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Information Problems in Venture Capital (VC) Markets

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FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT STRATÉGIE, GLOBALISATION ET SOCIÉTÉ

Information Problems in Venture Capital (VC) Markets

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de
Doctorat en Management

par

Ron RABI

Directeur de thèse
Prof. Jeffrey Petty

Co-directrice de thèse
Prof. Naomi Hausman

Jury

Prof. Paul André, Président
Prof. Christian Zehnder, expert interne
Prof. Veroniek Collewaert, experte externe

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Ron RABI

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Information Problems in Venture Capital (VC) Markets

sans se prononcer sur les opinions exprimées dans cette thèse.

Lausanne, le 04.07.2024

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and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
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Information Problems in Venture Capital (VC) Markets

Doctoral Dissertation

Ron Rabi

HEC Lausanne

Department of Strategy

שיר הרעות // חיים גורי

על הנגב יורד ליל הסתיו
ומצית כוכבים חרש חרש
עת הרוח עובר על הסף
עננים מהלכים על הדרך.

כבר שנה לא הרגשנו כמעט
איך עברו הזמנים בשדותינו
כבר שנה ונותרנו מעט
מה רבים שאינם כבר בינינו.

אך נזכור את כולם
את יפי הבלורית והתואר
כי רעות שכזאת לעולם
לא תיתן את ליבנו לשכוח

Contents

Acknowledgments

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Introduction

In this dissertation, I explore three strategic and financial dimensions of information problems in the venture capital (VC) market. These dimensions cover three segments of the broad VC industry, as presented by Gompers and Lerner (2004): (a) the subsidy market, where public authorities provide R&D support to emerging ventures to compensate for informational spillovers; (b) the deal market, where VC funds leverage tacit information from their networks to reallocate resources across portfolio ventures; and (c) the international acquisition market, where potential acquirers are exposed to new information of cross-border opportunities by observing their peers. Importantly, although each of the chapters pertains to a different transaction type, they are interconnected by the VC transaction cycle and the inherent information asymmetry that characterizes investments in technology ventures. Consequently, these problems and their respective solutions can determine the level of VC activity in the market.

The academic literature in management and economics highlights the information asymmetry between investors and innovators as the core challenge in financing innovation (Hall and Lerner (2010)). This occurs because potential investors are unable to assess the likelihood of a venture's success in developing a technology and its anticipated rewards (Kerr and Nanda (2015)). Thus, traditional investors (e.g., banks) are often deterred from providing necessary capital to technology projects. This capital gap is especially pronounced for early-stage ventures, which face high capital requirements but often lack a solid track record, tangible assets, or consistent revenue streams that could serve as collateral (Da Rin, Hellmann, and Puri (2013); Hall and Lerner (2010)).

The VC industry has evolved to bridge these information asymmetries and provide capital to early-stage technology ventures (Gompers and Lerner (2001)). This has led to the development of specialized operational procedures and contracting practices designed to manage the uncertainty that characterize these ventures (Sahlman (1990)). For instance, VCs leverage their extensive networks to discover new investment opportunities (Gompers, Gornall, Kaplan, and Strebulaev (2020); Sorenson and Stuart (2001)) and depend heavily on information signals to filter and select potential investments (Petty and Gruber (2011); Petty, Gruber, and Harhoff (2023)). Upon selecting an investment, they meticulously craft contracts to align entrepreneurs' incentives with the long-term objectives of the venture (Kaplan and Strömberg (2001)), and they often employ staged financing strategies to mitigate risks (Dahiya and Ray (2012)).

However, despite the pivotal role of VC funds in facilitating transactions, VC markets remain relatively rare on a global scale (Drucker (2017); Lerner (2013)) and are known for their high volatility (Janeway, Nanda, and

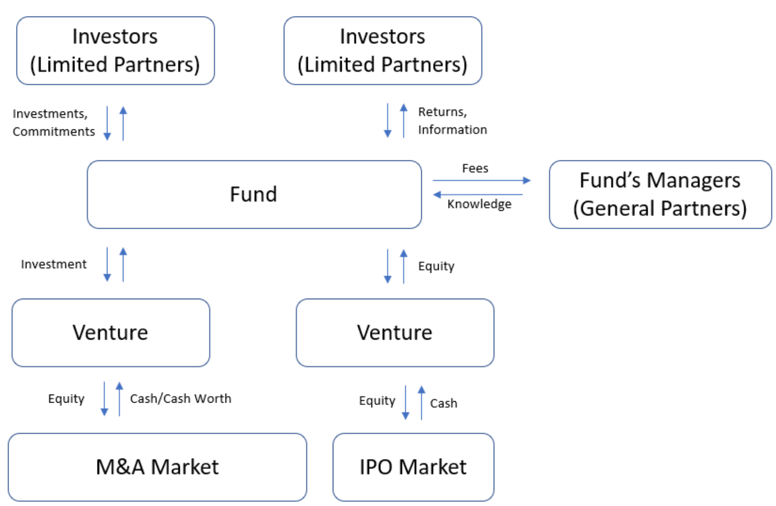
Rhodes-Kropf (2021); Zeira (1999)). An in-depth understanding of the factors influencing the operation of VC markets can illuminate this phenomenon, and provide valuable insights for policymakers, managers, and academics to facilitate and stabilize VC activity.

Thus, this dissertation examines critical elements of the VC cycle, highlighting how information problems at various stages can impact market dynamics. I specifically investigate how different stakeholders address information challenges throughout the extended VC market. Crucially, these frictions can exacerbate market volatility, as evidenced by the frequent booms and busts in the VC market, which are often triggered by seemingly external factors.

A prime example is how booms and busts in the VC market are triggered by public market conditions (Blass and Yafeh (2001); Gompers and Lerner (1999); Gompers, Kovner, Lerner, and Scharfstein (2008); Jeng and Wells (2000)). Notably, a downturn in public market returns reduces the likelihood that a VC-backed venture can successfully exit through an IPO or an acquisition, leading to decreased returns for the VC fund. This, in turn, results in a reduced inflow of new capital to the VC industry and to an inefficient termination of ventures (Kandel, Leshchinskii, and Yuklea (2011)). Similarly, conditions in labor markets (Jeng and Wells (2000); Marx (2022)), acquisition markets (Hellmann (2002); Higgins and Rodriguez (2006)), and the supply of ventures (Avnimelech and Teubal (2006); Poterba (1989)) are highly linked to levels of VC activity.

This market dynamic corresponds to the view of the VC industry as a cycle of transactions involving diverse actors (Gompers and Lerner (2004)). Figure 1 illustrates this cycle. Initially, capital from the fund's limited partners is injected into the fund and then allocated by the fund's general partners (i.e., managers) to ventures seeking investment, with the goal of liquidating these investments within 7-10 years. Ultimately, the returns from the liquidation of these ventures are distributed to the fund's limited partners, thereby initiating a new transaction cycle.

Figure 1: The venture capital cycle



Therefore, the existence and direction of the VC market are influenced by the various transactions depicted in Figure 1. Each of these transactions operates under a distinct set of information frictions. Addressing these frictions is essential for fostering a thriving VC market, while failure to address them may impact the rate and direction of VC activity and innovative work.

I hereby provide a more detailed overview of each chapter in my doctoral dissertation:

In Chapter 1, I investigate the role of governments in fostering R&D activities undertaken by emerging ventures through grant support. This form of support has been a common practice in OECD countries for over two decades and carries significant implications for the emergence of new ventures in the market (Trajtenberg (2002)), as well as for VC activity (Hall and Lerner (2010); Lerner (2013)). Both of which are linked to long-term economic growth (Da Rin et al. (2013); Griliches (1998); Romer (1990)).

However, the theoretical rationale for government intervention in R&D is revoked by the public good problem associated with R&D investments. Specifically, R&D generates knowledge spillovers that have broad social benefits but negative private returns (Arrow (1962)), leading to a systematic underinvestment in R&D by the private sector.

This study examines the varied impact of grants provided by the Israeli R&D agency on ventures. I use administrative data to examine the effect of the program on venture performance in the VC market. The analysis reveals heterogeneous effects of the program on ventures situated in markets where information frictions are significant and negative effects in relatively developed markets. Thus, this research contributes to a deeper understanding of the challenges faced by policymakers in fostering innovation through public interventions.

In Chapter (2), I investigate the impact of VC network referrals on a VC strategy. Specifically, this research examines how a network referral influences the availability and potential redistribution of resources across a VC's portfolio. This study contributes to a substantial body of literature that underscores the role of networks in mitigating information asymmetries in the VC market. Once established, VC networks are instrumental in exchanging private, tacit information, which is an important element in the investment decision-making process (Batjargal (2007); Burt (2002); Shane and Cable (2002); Shane and Stuart (2002)). A key mechanism for this information exchange is through deal-specific referrals, where VCs recommend particular investments to their network peers. Such referrals constitute approximately a third of all VC transactions (Gompers et al. (2020); Petty et al. (2023)), significantly reducing the resources needed for sourcing, screening, and selecting investments (Wang (2016)).

This study makes two main contributions to the empirical literature on network referrals in VC markets. First, it demonstrates that referrals not only reduce the costs associated with sourcing, screening, and selecting investments but also conserve monitoring resources during the post-investment phase. Second, it reveals that VCs leverage the resources saved through referrals by reallocating monitoring resources from referred to non-referred ventures within their portfolio. This strategic reallocation highlights the efficiency-enhancing potential of network referrals.

In Chapter (3), I investigate the phenomenon of herding in the context of cross-border acquisitions of Israeli ventures, prompted by the notable 2013 acquisition of Waze by Google. This event not only elevated the profile of Israeli ventures but also appeared to trigger a succession of similar high-value acquisitions by other major technology firms. Thus, the chapter examines whether seminal acquisitions stimulate the follow-on acquisition of similar ventures by peer acquirers.

Understanding these dynamics is valueable because while acquisitions represent the primary exit strategy for VC-backed ventures (Catalini, Guzman, and Stern (2019); Hellmann (2006)), they are fraught with uncertainties (Benson and Ziedonis (2010); Higgins and Rodriguez (2006)) that hinder this activity. The analysis in this chapter seeks to determine the extent to which initial successful acquisitions can alleviate these uncertainties and potentially stimulate a subsequent M&A activity.

The findings of this study demonstrate that corporate acquisitions in foreign markets act as a quality signal, encouraging further acquisitions within those markets. Specifically, it reveals that a venture's acquisition by a foreign firm significantly boosts the likelihood that a technologically similar peer will also be acquired by another foreign corporation. This effect is most pronounced in sectors experiencing their first cross-border acquisition and among foreign corporations with relatively weaker ties to the Israeli market, aligning with the notion of informational herding.

To conclude, this dissertation delves into the strategic and financial dimensions of information problems within the VC market, unraveling how these issues permeate the investment process and influence market dynamics. My investigation traverses three main areas: the effects of public R&D subsidies on emerging ventures, the impact of VC network referrals on resource allocation within VC funds, and the herding behavior in cross-border acquisitions of Israeli ventures. This comprehensive analysis highlights the significant role of information problems in the VC market and the various mechanisms employed to deal with those problems.

Throughout, the dissertation underscores the complex interplay between strategic behaviors driven by information access and the broader market implications. Government R&D subsidies, while boosting venture emergence and innovation, exhibit mixed impacts depending on market frictions. Network referrals within VC markets not only streamline investment processes by reducing the costs associated with venture screening and selection but also enhance portfolio management through strategic resource redistribution. Additionally, the study on cross-border acquisitions reveals how initial high-profile deals can trigger herding behavior, significantly shaping investment landscapes in technology sectors. These findings provide crucial insights for policymakers and industry stakeholders, emphasizing the need for targeted strategies to manage information problems and stabilize the inherently volatile VC market. Each chapter contributes to a nuanced understanding of how different stakeholders within the VC ecosystem navigate and leverage information asymmetries, ultimately influencing patterns of venture financing.

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Chapter 1

The Heterogeneous Impact of Government-Backed Venture Financing

The Heterogeneous Impact of Government-Backed Venture Financing

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Abstract

Public authorities regularly subsidize R&D ventures, but these support policies tend to fall short more frequently than they fulfill their promises. This study examines the influence of the Israeli program on ventures, utilizing administrative data from the Israel Innovation Authority (IIA), one of the most reputable innovation agencies worldwide. A contextual analysis reveals that market dynamics and firm heterogeneity are a source of operational complexity that undermine IIA's effectiveness in sponsoring R&D ventures. We find that grants are effective when market frictions are high, but crowd-out private funds when frictions are low. Thus, this research contributes to a deeper understanding of the challenges faced by policymakers in fostering innovation through public interventions.

1.1 Introduction

In an era characterized by rapid technological advancements, R&D ventures capture the attention of academics and policymakers in driving innovation, economic growth, and global competitiveness. Yet, tacit knowledge spillovers and financial frictions cause private markets to underinvest in R&D ventures than is socially optimal. In trying to bridge the gap between private and public returns, public authorities regularly subsidize R&D ventures.

Entrepreneurial hubs such as Silicon Valley, Singapore, and Tel Aviv are frequently cited as exemplary case studies illustrating how government support can catalyze the development of a prosperous venture capital market. However, these success stories seem to mislead policymakers by ignoring the nuanced and complex reality of government intervention. Lerner's work (2013), *"The Boulevard of Broken Dreams,"* succinctly captures the recent history of public efforts to incentivize R&D venture creation, revealing that many fail to deliver their promise. This observation underscores the operational challenges policymakers face in financing innovation.

Based upon this insight, we explore the impact of direct public support on the performance of R&D ventures in the VC market. Our detailed analysis delves into the nuanced and varied impacts of the support program across the venture market spectrum, focusing on the ex-ante quality distribution of ventures, as well as geographical and technological domains. We find significant variation in the program's impact, driven by differing levels of R&D intensity and access to VC opportunities, both of which influence the ability of ventures to raise funds. Thus, our research expands the understanding of the effectiveness of R&D grant policies.

Given these varying effects, we argue that evaluation studies should assess the effectiveness of the policy in different market environments. This observation challenges the prevailing literature, which often examines the average impact of R&D grants or uses regression discontinuity (RD) designs to evaluate the impact of R&D grant policies (e.g., Howell (2017)) around a random cutoff point of the venture distribution. Instead, a precise assessment should concentrate on localized effects throughout the venture-market spectrum and the venture quality distribution, particularly in areas where the ex-ante likelihood of receiving a grant is highest, rather than lowest.[1] This perspective shifts the focus from a generic evaluation to a more detailed understanding of grant impacts.[2]

To conduct this research we have collected administrative data from the Israel Innovation Authority ("IIA"). The analysis encompasses applications submitted to the IIA along with their corresponding financing outcomes, spanning fourteen years from 2006 to 2019. Applicants are required to submit a detailed R&D plan, including a comprehensive budget for the proposed project. Subsequently, the applications undergo a thorough evaluation process. A designated technology expert reviews each project, conducting on-site visits to assess the company's facilities and staff. Based on this assessment and a review of application documents, the expert provides a detailed report and assigns a score ranging from 1 to 5, with 0.1 increments. In the final stage, an R&D committee decides to grant or deny funding for the project. Grant recipients are eligible for up to 50% of the R&D budget endorsed by the committee.

[1] Sharp RD designs in a competitive context are structured to assess the local effect of an award where the ex-ante probability of receiving the award is lowest.

[2] For an in-depth review, please see section 1.2.

Leveraging this comprehensive dataset, we assess the impact of grants on venture survival alongside their performance in the venture capital market, particularly in securing follow-on funding rounds and the total capital raised. Our empirical approach utilizes a propensity score matching model to closely pair awarded and non-awarded projects based on similarity, focusing on matches within the same sector and year and maintaining a caliper of 0.2 standard deviations. This methodology significantly enhances the balance within our matched sample, providing a more robust foundation for analyzing the effects of grants on ventures.

We anticipate identifying a positive and significant impact in venture markets characterized by large financial frictions, which may stem from limited venture capital activity or high technological intensity. Specifically, within the context of financial frictions, a grant is expected to enhance a venture's capability to secure funding, thereby affecting the total amounts raised. Scenarios in which grants positively affect venture survival, yet simultaneously exert a negative influence on financial outcomes, are an indication of an inefficient allocation of resources by the grant agency.

We test these predictions across three venture contexts. First, across the ex-ante quality distribution of ventures, as indicated by the propensity score assigned to each project. This method identifies projects at the top of the distribution as associated with a higher R&D intensity and belonging to sectors with lower financial activity levels. As anticipated, we observe a more pronounced effect of the grant at the distribution's upper end, aligning with an efficient allocation of funds to projects.

Second, we examine the heterogeneous impact of the grant across four geographical regions, where we predict the most substantial effects in areas devoid of VC activity. We compare Tel Aviv, the main entrepreneurial hub in Israel where most VCs and ventures are located, to the Northern District of Israel, which hosts a large technical university and some international tech giants (e.g., IBM). We also examine Jerusalem, which has limited VC activity and a slowly growing technology market, and the Western Negev, where VC activity is lacking. Contrary to our expectations, the most significant impact was found in Tel-Aviv, where, ex-ante, there are low levels of financial friction. However, when considering ventures not at the technological forefront (as indicated by their position in the propensity score distribution), the most pronounced effects emerge in Jerusalem and the Western Negev. This finding aligns with our initial predictions.

Third, we examine the effect of the grant across technology sectors, where we expect the most significant effects in sectors plagued by a low level of VC activity and high R&D intensity. The analysis reveals that ventures operating within sectors experiencing financial frictions see positive effects from grants, while those in sectors with high levels of VC activity encounter negative effects. Nonetheless, accounting for projects at the top of the quality distribution, we also note mild positive effects in less constrained sectors.

In sum, this paper highlights the operational challenges involved with R&D grant programs, particularly in understanding the contexts that can impede the efficacy of R&D support policies. We demonstrate that even a successful market intervention policy is limited by the agency's ability to accurately identify markets and ventures where financial frictions hinder private R&D efforts. Importantly, we find significant variation in the program's impact across different venture markets, depending on the extent of financial frictions. Therefore, R&D grant policies should be tailored to regions and sectors based on a comprehensive understanding of their specific characteristics.

The remainder of the paper is organized as follows- Section 1.2 reviews relevant theoretical and empirical literature. Section 1.3 outlines the empirical context. Section 1.4 details the data and methodology employed. Section 1.5 describes the empirical identification strategy. Section 1.6 discusses the findings, and Section 1.7 provides concluding remarks.

1.2 Related literature

1.2.1 Theoretical background

The widely accepted justification for government support for R&D ventures stems from Arrow (1962)'s recognition of market failures, which lead private markets to underinvest in R&D. To a large extent, underinvestment occurs because knowledge spillovers to competitors hinder innovative firms from fully appropriating returns on their R&D efforts. Therefore, private return on R&D is typically lower than the social optimum (Griliches (1998)). Moreover, imperfect capital markets further exaggerate this return gap, as private investors are more uncertain of project success probabilities and potential outcomes, compared to innovators (Kerr and Nanda (2015)). This information asymmetry is particularly pronounced in R&D ventures compared to established firms (Hall and Lerner (2010)), since ventures lack a track record for reference in risk assessment and assets that may be used as collateral (Brown, Fazzari, and Petersen (2009); Hall and Lerner (2010); Hsu and Ziedonis (2013)). As a result, capital markets for R&D ventures are not likely to be efficient.

Public grants for R&D ventures aim to close this return gap by reducing the unit cost of R&D. In theory, an efficiently allocated grant would then increase the private return of a risky, yet socially valuable, R&D project that might otherwise have been abandoned (Dimos and Pugh (2016)). Therefore, these grants aim to incentivize private financiers to provide additional funding for R&D.

In a sense, public grant agencies are inherently risky investors, designed to compensate socially desired ventures for the expected risk of knowledge spillovers and zero collateral bankruptcy. Yet, grant programs are notoriously complicated to design and manage (Lerner (2013); Zhao and Ziedonis (2020)): First, these programs must exhibit adaptability to evolving market needs, avoiding rigid associations with predetermined industries or geographies. This requires the cultivation and retention of institutional market knowledge through continuous interactions with private financiers and entrepreneurs, along with a deep understanding of existing market conditions and failures. Specifically, policy outcomes may be influenced by R&D labor conditions, as a significant portion of R&D spending goes towards salary payments.[3] Therefore, subsidies directed towards inelastic R&D labor markets may lead to escalating wages rather than increasing R&D inputs (David and Hall (2000); Goolsbee (1998); Lach (2002); Trajtenberg (2002)).

[3] In practice 50% or more of R&D spending is allocated for hiring R&D personnel (Hall and Lerner (2010)).

Second, public agencies typically possess inferior information regarding a project's prospects compared to entrepreneurs, potentially leading to the adverse selection of projects with limited social value. For instance, Zhao and Ziedonis (2020), highlight the criticism faced by the U.S. SBIR program for incentivizing rent-seeking behavior, where ventures persist by continually seeking follow-on grant funding. Similarly, Wang, Li, and Furman (2017), note that China's Innofund program suboptimally financed "zombie projects" established by shall companies to attract public funding.

The results of Lach, Neeman, and Schankerman (2021) draw attention to the adverse selection problem, advocating for a focus on projects in the middle of the success probability distribution when structuring R&D grant programs. This recommendation stems from the idea that low-risk projects are more likely to attract private financing, and allocating public funds to them would diminish their social return. Conversely, high-risk projects are associated with a negative expected social return.

Ventures engaged in undesired, low-risk projects may exploit the availability of public funds when the cost of capital is low, especially when application costs are minimal and the probability of project selection is high (Aschhoff (2009)). Public grant programs, particularly conditional loan initiatives like the one under consideration, can mitigate this concern by adjusting interest rates (Lach et al. (2021)) or other financial components of the program, such as a royalty payment scheme.

Third, public agencies may face the temptation to award resources to projects with a low social value to enhance their public image (Czarnitzki and Lopes-Bento (2013); Lach (2002); Wallsten (2000); Zhao and Ziedonis (2020)). This situation bears resemblance to the tunneling problem identified by Johnson, La Porta, Lopez-de Silanes, and Shleifer (2000), where a controlling shareholder exploits a firm's assets for personal benefit. Similarly, a grant agency might engage in tunneling public funds to burnish its image, either by favoring commercially attractive projects, thus creating a misleading track record of success, or by awarding grants to suboptimal projects to generate headlines of "saving" jobs. Nonetheless, the identification of tunneling in this context requires a more comprehensive research approach which consists of qualitative efforts.

1.2.2 Empirical evidence

The central inquiry within the literature revolves around whether R&D grants spur or replace private R&D investment. An examination of earlier studies by David, Hall, and Toole (2000), yields inconclusive findings. Among the 33 studies reviewed, approximately one-third reported a crowding-out effect. Notably, Wallsten (2000), documented a complete crowding-out effect among participants of the U.S. SBIR program, while Lach (2002), found evidence of additionality only among young awardees of the Israeli grant program, with no significant effect observed for large firms. Additionally, Busom (2000), in Spain found that overall R&D subsidies do induce private funding, although roughly 30 percent of awardees experienced crowding out.

Critiques of this earlier body of research raise data and methodological concerns. David et al. (2000), report that most studies have overlooked selection issues related to the endogenous firm decision to apply for support or the agency's decision to grant it. Further, severe data limitations such as small samples (e.g., Busom (2000); Wallsten (2000)) or the absence of a comparable control group (e.g., Lach (2002)) limit the extent to which we can conclude from these results.

In a noteworthy observation, Becker (2015), highlights a discernible shift in the academic narrative, indicating an increase in the reported positive impacts of R&D grants. Dimos and Pugh (2016), corroborates this observation, yet adds a caveat that the additionality of these grants remains marginal and noisy. Intriguingly, Dimos and Pugh suggests that this emerging trend could be attributed to organizational learning processes. We propose that, to some extent, this shift is rooted in a broader shift in how R&D support programs are assessed.

In response to prior criticisms, recent academic efforts have concentrated on three key strategies: First, they have significantly improved data quality by sourcing administrative data on applicants directly from grant agencies, thus moving beyond the limitations of survey data from statistical offices and commercial data providers. Second, there has been a concerted effort to expand the range of evaluation metrics, incorporating a more diverse set of indicators beyond the traditional financial metrics. This expansion reflects a nuanced understanding that impacts on a firm's fundraising capabilities should be viewed as indicative of broader effects on R&D inputs (notably labor), outputs (such as patents), and overall firm performance. Third, the adoption of more rigorous methodologies has become prevalent, aimed at establishing stronger causal links and overcoming the methodological challenges highlighted in previous critiques.

For instance, Einio (2014), utilizes the geographical variation in government funding, governed by a population-density rule in Finland, to employ an instrumental variable approach. This strategy uncovers a notable positive impact of the R&D support program on R&D investments, employment, and sales.

A prevalent strategy involves accessing administrative data that contains application review ratings and utilizing these ratings within a regression discontinuity (RD) design. For instance, Howell (2017), employs a sharp RD to evaluate the impact of the U.S. Department of Energy's SBIR grant program on financing, patenting, revenues, and survival. The study reveals a significant effect of early-stage awards on investments and related outcomes. Howell, suggests that these effects are particularly pronounced for financially constrained ventures and attributes them to grants aimed at mitigating uncertainty through prototyping. Similarly, Bronzini and Iachini (2014), utilize a sharp RD design to evaluate the impact of a regional R&D program in Western Italy, reporting an additionality effect among small enterprises, while the overall reported effect of the program is null. Building upon this research, Bronzini and Piselli (2016), incorporate a larger sample and assess the impact of the programs on R&D outputs rather than inputs. They find a positive impact of the program on the number of patents and patent applications submitted by small recipients. Zhao and Ziedonis (2020), manipulate a sharp RD framework using data of the Michigan R&D loan program and report a positive impact on follow-on financing and survivability amongst small ventures. Lastly, Wang et al. (2017), in China use a fuzzy RD, where the probability of receiving a grant changes discontinuously around a random cutoff point. They find no effect of a grant on either financing, patenting, or survival of firms.

In light of its widespread application, RD research designs frequently reveal positive effects of R&D grants on small ventures across various metrics. Nonetheless, there are concerns regarding the disproportionate growth in the method's popularity as an evaluation tool. It appears that RD has become a ubiquitous term, enabling researchers to publish findings while sometimes overlooking critical methodological scrutiny. For instance, Howell (2017), and Zhao and Ziedonis (2020), have mechanically created a sharp RD design, while others (e.g. Howell (2017); Wang et al. (2017); Zhao and Ziedonis (2020)) have overlooked potential limitations in stacking semi-independent, normalized RD cohorts of the same program. Furthermore, as RD settings provide localized effects, there remains a lack of evidence regarding the non-marginal impact of government support programs. This is particularly significant considering that an optimal support program should target projects in the middle of the success probability distribution (Lach et al. (2021)). Therefore, if RD captures the effect in the "middle," it represents the upper bound of the aggregate effect of a policy.

In sum, the literature increasingly reports positive empirical findings on the impact of R&D programs, although these effects are often narrow in scope. The varied nature of these impacts is not yet fully understood, pointing to a gap in the research. Our analysis aims to shed light on the operational limitations of R&D grant policies, providing valuable insights for both academics and policymakers.

1.3 Contextual setting

Israel has gained global recognition for its high-tech sector, which has been at the forefront of global R&D efforts, maintaining the world's highest R&D to GDP expenditure for over two decades.[4] This notable achievement can be attributed to the extensive government support initiated by the IIA,[5] which harnessed the nation's substantial pool of scientific personnel that span out from Academia, the military's *"Lavi"* project, and the collapse of the USSR (Senor and Singer (2011)). Consequently, it comes as no surprise that Israel stands as a "laboratory case" exemplifying government intervention in R&D policy (Trajtenberg (2002)).

The IIA is mandated to boost the volume of R&D in Israel, with a prime focus on commercial R&D endeavors. Over the years, the IIA has introduced various programs, including the government-sponsored venture capital fund *"Yozma,"* which played a key role in initiating the thriving venture capital market in Israel. Other initiatives include the *"Incubators"* program, established in response to opportunities presented by the mass immigration of scientific personnel from the Soviet Union, as well as *"Magnet,"* designed to support generic, pre-competitive projects conducted by consortia of firms and academia, among others (Trajtenberg (2002)).

A key element of the IIA's strategic efforts is its grant scheme, dedicated to commercial R&D projects across the entire business spectrum. This program has been the mainstay of support for commercial R&D in Israel for the past twenty years, representing about two-thirds of the IIA's yearly budget with a significant investment of two hundred million dollars.[6] The program adopts a bottom-up approach during the application phase, ensuring

[4] OECD: Gross domestic spending on R&D
[5] formerly named: The Office of the Chief Scientist (OCS)
[6] Dollar amounts may vary based on ILS-USD exchange rates.

that grant applications arise organically from the market, untouched by centralized planning. Consequently, the application pool accurately mirrors market needs, rather than conforming to predefined administrative agendas.

R&D proposals can be submitted to the grant program at any point throughout the year, with the requirement that both the firm and its intellectual property (IP) are registered within Israel. Applicants must provide a comprehensive outline of their R&D project, detailing the plan, associated costs, projected commercial potential, information about the R&D team, and the division of labor. Once submitted, each application is subject to an extensive evaluation process. This includes an assessment by a technology expert, who reviews the materials and conducts a visit to the applicant's R&D facility. The expert compiles a detailed report and assigns a score ranging from 1 to 5, with increments of 0.1. A supervisory reviewer then scrutinizes these reports for any necessary adjustments. The final decision on fund allocation is made by a committee of public and government representatives, led by the Chief Scientist, who ensures the proposed R&D budgets are in line with IIA policies and sets the funding ratio.[7] Grant recipients are required to match the grant amount, covering the remainder of the approved budget.

When a company generates sales from an R&D project funded by a grant, it is required to repay the grant amount through royalties and interest based on the product's annual sales until full repayment is achieved. This repayment model functions as a conditional loan and acts as a deterrent, discouraging firms with commercially viable projects from applying for support (Lach et al. (2021)). It effectively prevents low-risk projects that have access to affordable capital from choosing a high-interest conditional loan. However, it has been suggested that modifying the IIA's interest rates could optimize this mechanism, ensuring it fulfills its purpose without imposing excessive burdens.[8]

1.4 Data

1.4.1 Data sources

We compile administrative data spanning two decades, starting in 2002, pertaining to applications submitted to the IIA's grant program. The research division at the IIA has anonymized the data to adhere to data protection provisions. Information on applications includes the application date, the requested R&D budget for the project, age of the applicant, a reviewer assessment score, a reviewer ID, an applicant ID, and a list of committee discussions held by the IIA, culminating in a final decision. These discussions predominantly revolve around either granting decisions or appeals related to prior granting decisions. Applications are categorized as grant recipients if a decision to allocate funds was made; otherwise, they are classified as "non-recipients." The definitive grant decision date corresponds to the first discussion to grant an application or the final discussion to deny it.

The IIA has supplemented our research with data on financial rounds sourced from the Israel Venture Capital (IVC) Research Center. As a key entity tracking the Israeli high-tech ecosystem since 1997, IVC provides additional insights into the characteristics of ventures in our sample, using data from 2004. The financial round

[7] Funding ratios range from 30% to 50% of the approved R&D budget

[8] Lach et al. (2021) discusses the potential benefits of modifying the IIA's interest rates to achieve a more effective balance.

data provided by IVC includes details such as the date of the round, a unique identifier, the venture's development stage, sector, and progress towards achieving sales. Furthermore, this dataset encompasses information about the financiers involved, offering a glimpse into their investment history, the nature of their investment (VC or otherwise), and their geographical origins.[9]

1.4.2 Sample selection

Given that the IIA's grant program allows applicants to submit multiple projects on demand, the initial database naturally contains confounding factors. To counteract this, we have refined the initial sample based on our research objectives, focusing on mitigating issues related to endogeneity.

Our analysis covers applications to the IIA's grant programs from 2006 to 2019, focusing particularly on "pivotal" submissions from young and inexperienced applicants. We define "pivotal" applications as those where the grant decision could have had a significant impact on the applicant's future. Considering the average project duration is two years, we employ a two-year criterion to assess the pivotal nature of an application. Accordingly, we include applications from recipients only if, within the two years leading up to the grant decision, the venture had not received support for any other project from the grant program. For non-recipients, an application is considered if the venture had not received support either in the two years before or after the decision on the application in question. Should a venture have more than two applications rejected within a two-year period or less, only the most recent rejected application is included in our analysis.

This algorithm is utilized for applicants characterized by a history of up to two prior projects, targeting those who are relatively inexperienced. Applicants possessing an extensive history of applications are often beyond the initial venture phase, overseeing a portfolio of projects that concurrently influence their financial results. Our methodology is designed to isolate the direct impact of grant receipt, minimizing the confounding effects of simultaneous project applications. This method is consistent with our empirical strategy, which involves matching grant recipients to non-recipients using firm-specific covariates. Allowing for overlapping projects within our analysis could lead to instances where two projects from the same venture are inadvertently paired through the propensity score matching algorithm.

Our analysis includes applications from ventures that are less than ten years old at the time of application, in line with our focus on early-stage ventures, which is central to our study's aims. While the choice of a ten-year threshold may appear arbitrary, it is consistent with similar research on early-stage ventures and follows the methodological definitions used by the Central Bureau of Statistics in Israel. The selection of the starting year for our sample is informed by legislative changes to the R&D act enacted by the Israeli parliament in 2006, allowing us also to incorporate two years of venture history from the Israel Venture Capital (IVC) Research Center. The requirement for the end year of the study is designed to ensure there is a minimum observation period of three years for assessing venture outcomes.

[9] All identifiers from IVC were anonymized by the IIA in adherence to data protection regulations.

Moving forward, we integrate the subset of IIA applicants with relevant data from IVC. Merging these datasets could introduce bias if IVC more readily identifies grant recipients than non-recipients. To address this, we illustrate the distribution of review scores in Appendix Figure A1.1, segmented by the merging outcome and the grant award status. The visual representation shows a marginal rightward shift in the density for non-recipients, suggesting that higher-quality submissions are somewhat more likely to be included in the IVC data. However, this shift is minimal and does not substantially compromise the integrity of our analysis or signal a significant selection bias stemming from IVC's data-gathering practices.

1.4.3 Outcome variables

The outcome variables evaluated in this study focus on two related measures of R&D inputs and a measure of venture survival. Three main arguments guide the decision to focus on input measures rather than output measures: First, input measures provide a clearer basis for evaluating whether subsidies complement or supplant private R&D efforts. Rather, output measures complicate the task of distinguishing the origins of these effects—whether they are privately or publicly generated. Second, an increase in R&D inputs is anticipated to boost R&D outputs, whereas the reverse relationship does not necessarily hold. Third, data on financing (an input measure) is more readily available compared to data on outputs, such as sales or intellectual property metrics, etc...

Consequently, the outcome variable evaluated in this study encompass: (a) Active$_t$ - a binary indicator variable set to one if a venture is still operational in a year $_t$ following the award decision date. (b) Follow on$_t$- a binary indicator variable set to one if a venture has raised a follow-on round from private investors.[10] (c) VC amount$_t$ - a continuous variable that measures the amount of money raised from private investors in the respective year after the award decision (in millions of dollars).

The expectation is that grants will positively impact the survival of budget-constrained ventures. However, an observed increase in venture survival could result from two contrasting scenarios. It may indicate an efficient allocation of grants, where funding mitigates the unique risks associated with a venture's R&D activities, enhancing its survival chances. Alternatively, it could suggest an inefficient allocation, where grants inadvertently prolong the existence of underperforming ventures that would otherwise face early termination. Therefore, when grants are allocated efficiently, we expect to see an increased ability to attract private financing. Conversely, in cases of inefficient allocation, the impact on a venture's capacity to secure funding is likely to be negligible or even negative.

1.4.4 Descriptive statistics

The final sample contains 1870 pivotal applications submitted to the IIA's grant program by young and inexperienced ventures between 2006 and 2019. Of these, 693 went unfunded. The remaining 1177 applications were

[10]Here, private investors refer to those who operate in the Israeli VC market and are tracked by IVC. Examples include Angels, venture-capital, venture-debt, corporate VC, etc.

backed by the grant program.

Table 2.2 presents summary statistics of the IIA's sampe of pivotal applications. In Panel A, differences between grant recipients and non-recipients are evident in observed covariates. Recipients, on average, propose larger R&D projects, seeking a budget of 4.7 million ILS[11] compared to the 4.3 million ILS requested by non-recipients. Moreover, recipients are more likely to secure VC financing, and the assigned reviewer awards them a higher score (3.7 vs. 2.9 for non-recipients).

Panel B presents data on observed venture outcomes, revealing that grant recipients consistently outperform non-recipients. Specifically, recipients are 5% more likely to remain operational three years following the grant award. Furthermore, their chances of obtaining follow-on funding from private investors increase by 9% within a year of receiving the grant and by 14% after three years. This enhanced ability to attract private capital is quantified as an average increase of 1.66 million dollars in the first year and 2.67 million dollars after three years. The descriptive statistics underscore substantial differences between grant recipients to non-recipients. Our study seeks to distinguish the causal impact of the grant from potential confounding factors.

1.5 Empirical identification

This study examines the impact of the Israeli grant program on early-stage ventures, specifically focusing on how the policy's effects vary across different pre-grant success probabilities and venture environments. We aim to identify the markets, regions, and venture characteristics that are most significantly affected by grants, providing insights that could help policymakers in grant agencies to devise more targeted and effective programs. Moreover, we posit that exploring the influence of grants across a pre-existing quality distribution offers a valuable addition to the empirical body of work in this field, potentially enriching our understanding of the strengths and weaknesses of common evaluation tools.

In an ideal evaluation scenario, concerns related to selection bias would be mitigated by the random assignment of grants to applicants. This approach would enable an assessment of policy effects without the worry that a venture's application status is systematically correlated with other factors affecting its performance. However, in alignment with the nature of observational public policy studies, the allocation of funds to ventures is non-random. Grants are allocated to R&D projects following a thorough evaluation by a reviewer and subsequent assessment by a research committee. Hence, venture performance and grant award status are indirectly correlated.

To address concerns related to endogeneity arising from selection bias, our study employs a propensity score matching (PSM) algorithm. PSM is a statistical method frequently used in observational studies to minimize selection bias by estimating the probability (propensity score) that an observation will receive a particular treatment. This facilitates the matching of treated and untreated units that are similar, thereby creating a more balanced comparison group (Abadie and Imbens (2016)). This approach significantly mitigates the influence of confounding variables and strengthens the study's internal validity. Additionally, PSM enables us an in-depth analysis of

[11] New Israeli Shekel

the effects of grants across different levels of propensity scores. Consequently, our research goes beyond merely identifying local treatment effects as seen in regression discontinuity (RD) studies and average treatment effects commonly reported in the literature, thereby providing a fuller assessment of the grant program's impact.

$$\begin{aligned} \mathrm{Y}_i =& \beta_0 + \theta_0 \text{Award Status}_i + \beta_1 \text{Review Score}_i + \beta_2 \text{Review Score}_i^2 + \beta_3 \ln(1\text{+ Req. Budget}_i) \\ &+ \beta_4 \text{Age}_{i0} + \beta_5 \text{VC Amount}_{i0} + \text{FEs}_q + \epsilon_i \end{aligned} \tag{1.1}$$

We estimate the Average Treatment Effect on the Treated (ATT) based on the baseline empirical model outlined in Eq. 1.1, where Y denotes the venture's post-grant performance outcome. The subscript i refers to a specific R&D project. The binary variable *Award Status*$_i$ is 1 for projects that were awarded a grant (grant recipients) and 0 for non-recipients. *Review Score*$_i$ reflects the reviewer evaluation score, ranging from 1 to 5, while Review Score$_i^2$ represents the square of this score. The term $\ln(1 + \textit{Requested Budget}_i)$ captures the logarithm of the R&D budget requested in millions of ILS. Age$_{i0}$ denotes the age of the venture pursuing the R&D project at the time of the final award decision, and *VC Amount*$_{i0}$ represents the millions of dollars raised from private investors by the venture. *FEsq* includes fixed effects for the discussion year interacted with the venture's technological sector and a fixed effect for the ex-ante round stage of the venture prior to the award decision date.

1.5.1 Calculating propensity scores

Following the baseline model, Eq. 1.2 describes the first stage of the PSM model, which calculates a propensity score for each R&D project in our sample. This is done by regressing the treatment variable against the vector of covariates outlined previously. The outcomes of this first-stage regression are detailed in Table 1.2. Notably, the results from this stage highlight the reviewer's score as the most significant determinant of a project's likelihood of securing a grant.

$$\begin{aligned} \text{Award Status}_i =& \beta_0 + \beta_1 \text{Review Score}_i + \beta_2 \text{Review Score}_i^2 + \beta_3 \ln(1\text{+ Req. Budget}_i) \\ &+ \beta_4 \text{Age}_{i0} + \beta_5 \text{VC Amount}_{i0} + \text{FEs}_q + \epsilon_i \end{aligned} \tag{1.2}$$

Figure 1 presents the joint distribution of propensity scores and reviewer evaluations. In Panel A, a color-coded scheme highlights the final grant status for each project, revealing that higher reviewer scores are associated with higher propensity scores. This panel effectively demonstrates the propensity score's ability to predict grant success, evidenced by a denser concentration of grant recipients in the top right corner as opposed to the bottom left. Panel B then segments the analysis into two periods: before and after 2016, showcasing a notable rightward shift in propensity scores over time. This shift signals an increasing difficulty in securing grants in more recent years. We consider this shift in refining our matching algorithm.

1.5.2 Matching

After calculating propensity scores, we use a matching algorithm to pair grant recipients with non-recipients. Specifically, we implement a nearest-neighbor matching approach, utilizing a caliper of 0.2 standard deviations to ensure the similarity of pairs. To further refine the balance of our matched sample, matches are allowed within the same sector and year. To broaden the potential for matches, we also consider projects from one year before or after the focal year, as long as they fall within the same program period (i.e., before or after 2016).[12] This tailored approach aims to maximize the comparability of matched pairs, taking into account the specific limitations of our data. Subsequently, we categorize each observation into one of five quintiles based on its propensity score.

Figure 2 outlines the joint distribution of propensity and review scores by detailing quintile-based matching outcomes. Panel A reveals that the algorithm struggled to find matches for treated units mainly in the 5th quintile, where grant likelihood exceeds 80%, pointing to a shortage of control units in this high-probability group. Panel B displays matched treated units, showing an expected uptick in matches as propensity scores rise. In Panel C, matched control units are visualized, with circle size indicating multiple matches per control. This phenomenon is more prevalent in the top quintile, reflecting the scarcity in control units. Panel D highlights unmatched control units, predominantly in the lowest (1st) quintile, where the chance of receiving a grant is below 20%. Overall, this figure illustrates the matching challenges at both spectrum ends, with multiple unmatchable controls in the lowest quintile and frequent re-matched controls in the highest quintile.

1.5.3 Assessing balance

Figure 3 illustrates the improved balance among covariates used to calculate propensity scores. In Panel A, we examine the matched sample's balance across five quintiles. Sub-panel A.1 displays the p-values obtained from the difference between treatment and control units, for both the full and matched samples (shown in white and black, respectively), allowing us to observe the relative improvement in the sample's balancing. Sub-panel A.2 details changes in the standardized mean difference. Balance is achieved in Sub-panel A.1 when p-values are above 0.1, indicating a statistically insignificant difference between treated and control groups. Similarly, in Sub-panel A.2, balance is achieved when the absolute standardized mean difference falls below 0.1. The results in Panel A show significant improvements in the matched sample's balance, particularly regarding the venture's age and both the review score and its square. However, our algorithm has not succeeded in improving the sample's balance for the logarithm of the requested R&D budget and the funding secured from private investors.

Our concern is that the extreme quintiles—namely the first and fifth—might be disrupting the balance of our matched sample due to their low match likelihood and frequent matching outcomes.[13] To delve deeper, Panel B

[12] refer to Panel B in Figure 1

[13] This issue is frequently encountered in PSM studies, which compels researchers to direct their analyses towards the "common support" region. This region is defined as the span within the propensity score distribution where both the treatment and control groups exhibit sufficient

presents an analysis focused on the balance within the common support area, honing in on the second, third, and fourth quintiles. This additional assessment verifies that the matched sample within these central quintiles achieves notable balance across all covariates, evidenced by significant improvements in p-values and standardized mean differences. Given our interest in the extreme quintiles, our analyses will alternate between the two matched samples. Moreover, to address the remaining concerns of endogeneity in the matched samples, our analysis will incorporate all relevant covariates from the first-stage regression into the second-stage.

Finally, Table 1.3 offers a comparative overview of the two matched samples against the original full sample. Panel A indicates that out of 1094 matched projects, 484 are situated within the middle quintiles. The number of unique observations across all quintiles (1 to 5) in the matched sample stands at 384, in contrast to 207 unique observations in the narrower range of quintiles 2 to 4. This distinction underscores the frequency with which projects in the extreme quintiles are matched multiple times. Panel B provides a breakdown into economic classifications of regions, showing that projects from Tel-Aviv and the central district are the majority in all samples, comprising between 76-81% of the full sample. The Western district and Jerusalem collectively contribute to around 19%, while the Western Negev makes up about 2% of the projects.[14]

Panel C details the distribution of projects across sectors. The original IVC database identifies 8 sectors, yet our matching process encompasses only 4 due to limited observations in the others. These 4 sectors represent 76% of the full sample. Specifically, the Communication sector comprises 11% of the full sample but only 4% of the matched samples. IT & Enterprise Software makes up 22% of the full sample, with a slight overrepresentation in the matched samples. Life Sciences accounts for 34% in the full sample, significantly increasing to 62% in the matched samples. Lastly, Miscellaneous Technologies represent 9% of the full sample and 3% of the matched samples.

Panel D emphasizes differences in the distribution of projects across propensity score quintiles. In the extended (1-5) matched sample, there's a significant peak in the fifth quintile, with approximately 50% of projects concentrated there. When excluding the extreme quintiles in the narrow matched sample, focusing on the common support area, the 4th quintile emerges as the largest one, encompassing 43.8% of projects.

1.6 Results

This section outlines the key findings from evaluating the impact of government grants on venture performance. Our analysis focuses on the effectiveness of the grants in stimulating private R&D funding and enhancing venture survival. Initially, we present the results from a naive regression model that includes all ventures from our full non-matched sample, as outlined in section 4.2. Subsequently, we examine the grant's effectiveness within a PSM framework. The core of our analysis investigates the grant's heterogeneous effects in various contexts. Specifically, we explore how the impact of grants varies across the propensity score distribution, technological sectors, and

representation (Caliendo and Kopeinig (2008)).

[14] Percentages may vary slightly across samples; please refer to the table for precise figures.

geographical regions. We anticipate a positive influence ($\theta_0 > 0$) of grants on ventures' ability to survive, secure follow-on funding, and attract larger investments. Consistent with the theoretical framework discussed in section 2.1, we expect the most significant effects in environments with greater financial frictions.

1.6.1 Naive regression results

Table 1.4 showcases the naive estimates of the impact of grants on venture performance, based on the model outlined in Eq. 1.1. A priori, the results of this model may suffer from some level of endogeneity, since the allocation rule of funds to ventures is non-random. However, the introduction of our novel set of controls—including a reviewer evaluation score, the proposed project's budget, the venture's age, and the amount of capital raised from VC investors, along with fixed effects for sector-year and the venture's ex ante round level—aims to mitigate this concern.

Our findings indicate a positive and significant effect, represented by θ_0, on the likelihood of a venture's survival and its ability to secure follow-on funding from private investors after receiving a government grant. Reflecting on these moderate results in light of the descriptive statistics presented in Table 2.2, it becomes evident that our set of controls is effective in mitigating endogeneity. Specifically, we find that ventures receiving government support demonstrate a 7.1 p.p increase in their survival chances three years after the grant, though the first year shows no significant effect. Moreover, these ventures are 7.7 p.p and 8.4 p.p more likely to secure follow-on funding from private investors in the first and third years, respectively, after the grant. However, this increased likelihood of receiving follow-on rounds does not equate to a larger amount of capital raised in the VC market. This suggests a potential trade-off between the scope (extensive margin) and scale (intensive margin) of the government's influence on venture financing.

1.6.2 PSM results

Table 1.5 presents ATT estimates considering the impact of a grant on venture performance, and leveraging the extensive matched sample described in section 5.[15] We adjust Eq. 1.1 to include a pair-level fixed effect.

The findings from this analysis reveal a more pronounced effect compared to the naive estimates shown in Table 1.4. Specifically, we observe an additional 2.6 p.p increase in the impact of grants on venture survival three years after obtaining a grant, resulting in a total effect of 9.15 p.p. Similarly, grant recipients show an increased likelihood of securing a follow-on round, this effect totals at 10 p.p and 17.4 p.p after one and three years, respectively. However, these significant effect sizes do not lead to a corresponding increase in the amount of funding raised in the first year after receiving the grant. Intriguingly, on average, grant recipients raise 6.3 million dollars less three years down the line. This suggests that while a grant can make a venture more attractive to private investors, it may concurrently crowd out dollar investment amounts.

[15] We refer here to the matched sample encompassing quintiles 1-5.

1.6.3 Heterogeneous quintile effects

This subsection examines the heterogeneous effect of a grant on ventures across an ex-ante quality distribution. Theory accounts posit that the impact of grants is most pronounced at the midpoint of the distribution of the ex-ante commercial success probability. This is where the barrier of technological innovation often discourages risk-averse investors from funding ventures. However, given that the ex-ante commercial quality is not directly observable, our analysis focuses on the distribution of propensity scores instead. This approach allows us to assess the efficacy of the IIA's allocation rule. An effective allocation policy would be indicated by progressively larger effects corresponding to higher propensity scores.[16]

To test this, we modify Eq. 1.1 to account for heterogeneity in the treatment effect. The refined model is presented in Eq. 1.3:

$$
\begin{aligned}
\text{Y}_i =& \beta_0 + \theta_0 \text{Award Status}_i + \theta_1 \text{Award Status}_i * \text{1st quintile}_i + \theta_2 \text{Award Status}_i * \text{2nd quintile}_i + \\
& \theta_3 \text{Award Status}_i * \text{3rd quintile}_i + \theta_4 \text{Award Status}_i * \text{4th quintile}_i + \beta_1 \text{Review Score}_i + \beta_2 \text{Review}_i^2 + \\
& \beta_3 \ln(1\text{+ Req. Budget}_i) + \beta_4 \text{Age}_{i0} + \beta_5 \text{VC Amount}_{i0} + \text{quintile FE} + \text{FEs}_q + \epsilon_i
\end{aligned} \tag{1.3}
$$

Table 1.6 displays the estimated coefficients of each quintile from the heterogeneous model outlined in Eq. 1.3. For clarity, alongside each quintile effect, we note the corresponding coefficient notations. Columns (1) and (2) examine the differential effects of grants on venture survival probabilities. The findings underscore a statistically significant impact (at the 1% level) and economically meaningful influence on the survival rates of ventures located at the lowest and highest quintiles, three years after grant receipt. Specifically, ventures in these quintiles experience an 18 and a 16 percentage point increase in survival chances, respectively, compared to their non-recipient counterparts within the same quintile. Conversely, impacts observed in the intermediate quintiles are generally minimal and statistically non-significant.

Next, we assess in columns (3) and (4) the heterogeneous effect of the grant on the ability to secure a follow-on round from private investors. Our findings reveal a substantial and statistically significant effect on ventures in the top quintile, experiencing an increased likelihood of 22.8 and 38.2 p.p in raising a follow-on round one and three years, respectively, after being awarded a grant. However, the effects observed for the intermediate quintiles are again largely negligible, whereas, in the bottom quintile, the impact is negative in the first year and turns positive in the third, yet remains statistically insignificant in both instances.

Examining the influence on funding amounts secured from VC investors, in columns (5) and (6), our analysis suggests that grants may displace private financing within the initial four quintiles, with a considerable variation in the magnitude of this effect. Meanwhile, grant recipients in the top quintile secure, on average, 2.5 million dollars more than their non-recipient peers, yet these effects are statistically insignificant at conventional levels.

[16] Note that the propensity scores reflect the estimated probability of receiving a grant, based on the IIA's allocation criteria as detailed in Table 1.2.

These findings indicate that the IIA's allocation policy is generally efficient, albeit with minor inefficiencies noted around the intermediate quintiles. The adverse outcomes observed for grants in the lower quintiles could be interpreted as efficient, given that the probability of receiving a grant in these quintiles is less than the probability of being declined.

However, a limitation of the analysis conducted herein lies in the substantial imbalance introduced by the top and bottom quintiles,[17] raising concerns that our findings might be more reflective of sample imbalance than the actual effect of grants. To address this concern, Figure 4 presents a detailed profile of the average venture within each quintile. In Panel A, we provide data on review scores, including two of its sub-components - a technology and an economic score. While the overall review score is available for the full sample, the sub-component scores were manually collected for a separate project and only cover ventures applying for support between 2006 and 2010. This data reveals that ventures in the top quintile are awarded higher technology scores, consistent with these ventures operating under financial frictions. Panel B details the quintile average of financial activity in affiliated sectors. This panel indicates that ventures in the top quintile tend to operate in sectors characterized by greater financial frictions as measured by the number of deals and their total amounts. Collectively, the findings from this subsection suggest a favorable effect of grants on ventures located in the top quintile, characterized by high R&D intensity and market frictions.

1.6.4 Regional effects

Moving forward, we examine the heterogeneous effect of a grant on ventures across geographical locations. We differentiate between four regions, according to their socioeconomic classification provided by the Israeli government.[18] The regions considered are: Tel-Aviv and the central district, the Northern district, Jerusalem, and the Western Negev region.

Israel's VC activity varies significantly across these regions. Tel Aviv and the Central District, the epicenter of the nation's tech ecosystem, boast a high concentration of ventures, VCs, and global tech giants, supported by robust infrastructure and a culture of innovation. In contrast, the Northern District, anchored by the Technion – Israel Institute of Technology, features fewer VCs and a more dispersed entrepreneurial network, though it benefits from strong educational institutions and large R&D labs of tech giants as IBM. Jerusalem's smaller but growing ecosystem focuses on sectors like med-tech and transportation, supported by incubators and innovation centers, yet faces limitations in VC activity compared to Tel Aviv. The Western Negev Region lags behind, with sparse startup activity, limited VC presence, and fewer technological resources, despite efforts to leverage local strengths in agriculture and sustainability.[19]

Following the financial frictions logic, we expect to observe the largest effect in Jerusalem and the Western Negev region, where the density of R&D centers, ventures, and venture capital funds is lower.

[17] See sub-section 1.5.3

[18] The designated socioeconomic classification into regions is not mutually exclusive. A city within the central district may fall under a different classification if it operates under a different socioeconomic environment.

[19] Appendix Table A1.1 provides summary statistics of each region.

To test this, we modify Eq. 1.1 to account for heterogeneity in treatment effects across regions. The refined model is presented in Eq. 1.4:

$$\begin{aligned}
\mathrm{Y}_i =&\beta_0 + \theta_0 \text{Award Status}_i + \theta_1 \text{Award Status}_i * \text{Northern District}_i + \theta_2 \text{Award Status}_i * \text{Jerusalem}_i + \\
&\theta_3 \text{Award Status}_i * \text{Western Negev}_i + \beta_1 \text{Review Score}_i + \beta_2 \text{Review}_i^2 + \\
&\beta_3 \ln(1\text{+ Req. Budget}_i) + \beta_4 \text{Age}_{i0} + \beta_5 \text{VC Amount}_{i0} + \text{Region FE} + \text{FEs}_q + \epsilon_i
\end{aligned} \tag{1.4}$$

Table 1.7 presents the coefficient estimates derived from the heterogeneous model described in Eq. 1.4. Panel A of this table illustrates the findings across the extended matched sample, encompassing quintiles 1 through 5. Columns (1) and (2) explore the differential effect of a grant on venture survival. The results from column (1) show a statistically and economically negligible impact of the grant on the survival of ventures from Tel-Aviv, the Northern district, and Jerusalem, with a 13 p.p increase in the probability of ventures from the Western Negev surviving the first year, although this result does not reach statistical significance. In column (2), we find a positive and significant effect on the long-term survival of ventures from Tel-Aviv, the Northern district, and the Western Negev, corresponding to a respective increase of 9.55 p.p ($p<0.01$), 21.54 p.p ($p<0.01$), and 28.81 p.p ($p<0.05$). Interestingly, ventures from Jerusalem experience an 18.3 p.p decline in their survival probability after being awarded a grant.

Shifting our focus to columns (3) and (4), the analysis extends to the varied effect of a grant on securing follow-on funding rounds. Notably, ventures based in Tel-Aviv show a significant increase in their likelihood of obtaining a follow-on round, with a 10.2 ($p<0.01$) and a 20.6 p.p ($p<0.01$) increase one and three years post-grant, respectively. Similarly, Jerusalem-based ventures exhibit a 33.04 p.p increase ($p<0.01$) in the probability of raising a follow-on round in the year after receiving a grant. However, this effect diminishes by half and becomes statistically insignificant in the third year. In the case of ventures from the Western Negev, there is a noted positive effect of 21.7 p.p in the first year and 27.04 p.p in the third year post-grant, although these effects do not achieve statistical significance. On the other hand, ventures from the Northern district witness a non-significant average decrease of 10.8 p.p in their chances of raising a follow-on round three years after receiving the grant.

Lastly, in columns (5) and (6) we examine the impact of the grant on the dollar amounts raised from private investors in the VC market. The results here vary across regions, both in terms of their direction and intensity. Specifically, ventures located in Tel-Aviv witness a notable decrease, averaging a reduction of 7.7 million dollars in capital raised three years post-grant, an outcome that holds statistical significance at the 1% level. Conversely, ventures from the Northern district encounter a lesser decline, with an average of 4 million dollars less capital raised compared to their counterparts, though this result does not reach statistical significance. For ventures based in Jerusalem, the grant's effect is negligible in economic and statistical terms. Meanwhile, ventures from the Western Negev region present a contrasting trend, with an average increase of 15 million dollars in raised capital compared to their non-awarded peers, albeit this finding also lacks statistical significance.

Panel B of Table 1.7 focuses on the narrow-matched sample, including ventures from quintiles 2 through 4. Focusing on these quintiles allows us to mitigate the bias stemming from the over-representation of ventures, particularly those in the top quintile, within the Tel-Aviv region. Moreover, it facilitates a more nuanced analysis by distinguishing between financial frictions related to regional characteristics as opposed to those tied to technological intensity.[20]

The analysis shows that grants awarded to ventures in Tel-Aviv and the Northern District lead to reductions in private dollar investments of \$19.8 million ($p<0.01$) and \$4.6 million ($p>0.1$), respectively, three years after the grant. In Tel-Aviv, the impact of grants on the likelihood of receiving follow-on funding rounds is negligible. The Northern district, on the other hand, experiences negative impacts of 17.2 and 33.5 million dollars, though these are not statistically significant. Contrarily, ventures in Jerusalem benefit significantly from grants, demonstrating a 50 p.p increase in their ability to secure follow-on rounds and a \$2.5 million increase in funds raised ($p<0.05$) one year post-grant, with these effects vanishing after three years. The Western Negev displays a positive effect of the grant on venture survival, follow-on rounds, and raised funds within the first three years post-grant, though the latter does not reach statistical significance. To a certain extent, that may be attributed to the small sample size of ventures from this region, which may explain the inflated coefficients and standard errors.

Overall, the analysis of the diverse impact of grants across geographical regions reveals two primary findings. First, the allocation of grants to ventures located in Tel-Aviv, an area with lower ex-ante market frictions, proves effective primarily for ventures positioned at the top of the propensity score distribution. As discussed in the previous subsection, these ventures undertake more intensive R&D projects, thereby affecting their expected private return due to significant knowledge spillovers. Second, when considering ventures not at the forefront of technology development, grants are more effective in regions with lower levels of VC activity.

1.6.5 Sectoral effects

We conclude our analysis by exploring the varied impact of a grant across different technology sectors. IVC categorizes ventures into eight technology sectors: Agritech, Cleantech, Communications, IT & Enterprise Software, Internet, Life Sciences, Miscellaneous, and Semiconductors. The matching algorithm detailed in Section 1.5.2 was effective in identifying suitable matches only in four sectors: Communications, IT & Enterprise Software, Life Sciences, and Miscellaneous.[21] Collectively, these sectors comprise 77% of the entire pre-matched sample, thereby forming the core of the grant program.

Figure 5 presents average venture characteristics, by affiliated sector. As before, Panel A details the review scores, while Panel B sheds light on the level of financial activity within each sector, by averaging the number and total volume of transactions over time. This enables us to establish expectations of the coefficient values for this

[20] The ventures in the top quintile often face financial frictions more closely related to their technological aspects. By refining the sample to exclude these quintiles, the analysis shifts towards understanding financial frictions attributable to geographical factors.

[21] Definitions for these sectors can be found in Appendix Table A1.2 for the matched sectors, and Appendix Table A.1.3 for the non-matched sectors

analysis. Consistent with the notion of financial friction, we predict that sectors experiencing more severe financial constraints to exhibit the most significant effects, and those under lesser constraints to show minimal, or negative effects. Examining the statistics in Figure 5, the IT & Enterprise Software sector emerges as the least financially constrained, both in terms of the technology review scores and the average number and sum of deals. Meanwhile, the other three sectors exhibit comparable attributes, except for the Life Sciences sector, which stands out due to a higher influx of funds. Thus, we expect to observe the highest effects in Communications and Miscellaneous, followed by the Life Sciences sector. The lowest effect size is expected for the IT & Enterprise software.

To test this, we modify Eq. 1.1 to account for heterogeneity in the treatment effect by sector affiliation. The refined model is presented in Eq. 1.5:

$$\begin{aligned} \text{Y}_i = &\beta_0 + \theta_0 \text{Award Status}_i + \theta_1 \text{Award Status}_i * \text{Communications}_i + \theta_2 \text{Award Status}_i * \text{IT \& Ent. Soft.}_i + \\ &\theta_3 \text{Award Status}_i * \text{Miscellaneous}_i + \beta_1 \text{Review Score}_i + \beta_2 \text{Review}_i^2 + \beta_3 \ln(1\text{+ Req. Budget}_i) + \\ &\beta_4 \text{Age}_{i0} + \beta_5 \text{VC Amount}_{i0} + \text{FEs}_q + \epsilon_i \end{aligned} \tag{1.5}$$

Table 1.8 showcases the results obtained from this analysis. The table presents coefficient estimates derived from the model outlined in Eq. 1.5. Panel A presents the findings for the wide-matched sample, and Panel B focuses on the results for the narrow-matched sample. Within Panel A, the analysis highlights the positive impact of grants on ventures in the Communications sector, aligning with our initial hypotheses. Specifically, ventures receiving grants in this sector experience a 16.8 p.p increase in their one-year survival probability ($p<0.05$) and a 13.7 p.p increase at the three-year mark, though the latter is not statistically significant ($p>0.1$). At the financial level, these ventures exhibit a 20 p.p boost in their likelihood of securing a follow-on funding round within both one and three years post-grant. This amounts to a 4 million dollar increase in additional funding secured by these ventures.

Contrasting with the findings for the Communications sector, ventures within the Miscellaneous technologies category experience predominantly negative effects, although these results are insignificant for the financial outcomes. Notably, ventures in this category have a 30 p.p higher chance of surviving after three years, a statistically significant estimate at 5%. However, their chances of obtaining follow-on funding rounds decrease by 11.8 and 24.3 p.p after one and three years, respectively. Consequently, there's an observed average reduction of 2.5 million dollars in funds raised in the first year, extending to 11.9 million dollars by the third year.

Shifting focus to the remaining sectors, IT & Enterprise Software and Life Sciences, our analysis suggests a discernible crowding-out effect. Notably, there's an observable trend towards increased survival rates and an enhanced probability of obtaining follow-on funding rounds within these sectors. Despite these positives, the presence of grants seems to negatively impact the volume of capital raised in subsequent VC funding rounds. Specifically, ventures within the IT & Enterprise Software and Life Sciences sectors see a reduction in the amount of long-term funding by 10.5 million dollars ($p<0.05\%$) and 4 million dollars ($p<0.05\%$), respectively, relative to their counterparts in the same sectors.

In Panel B, we present the results for ventures situated in the narrow-matched sample, which reinforce our initial expectations and the findings provided in Panel A. Specifically, we observe a pronounced crowding-out effect in the IT & Enterprise Software and Life Sciences sectors, where the grant's influence on both survival rates and the capacity to secure follow-on funding diminishes entirely. This crowding-out effect quantifies to 30 million dollars ($p<0.01$) for IT & Enterprise Software and 9 million dollars ($p<0.05$) for Life Sciences after three years. Conversely, in the Communications sector, the grant's positive impact on survival escalates to a 23 p.p increase in the first year and a 20 p.p increase in the third year. Moreover, the effect on the ability to secure a follow-on round in the first year surges to a 34 p.p increase, significant at the 1% level, although the third-year effect wanes to a 10 p.p increase, losing significance. However, the average funding amount raised by grant-awarded ventures in the Communications sector drops to an average negative effect size of 8.3 million dollars, with noted high volatility.

In the Miscellaneous sector, the grant shows no discernible effect on survival or on securing follow-on funding. Nevertheless, a positive impact is seen in the funding amounts raised, with an average increase of 1.6 million dollars ($p<0.1$) in the first year and a substantial 20.9 million dollars in the third year, narrowly missing conventional significance markers.

Collectively, these findings suggest that the impact of grants on ventures varies significantly across sectors, becoming more pronounced in sectors facing financial constraints. However, for sectors less financially constrained, the effects intensify for ventures at the higher end of the propensity score distribution. This, we believe, is attributed to the increasing R&D intensity of projects at the top propensity score quintile, which increases these projects' financial frictions, as discussed in subsection 1.6.3.

1.7 Conclusions

In this study, we set out to examine the efficacy of public R&D support in catalyzing venture success within the VC market, with a particular focus on the Israeli grant program. Our research findings offer a nuanced perspective on the impact of these grants, suggesting that their effectiveness varies significantly across different venture contexts, including ex-ante venture quality, geographical regions, and technology sectors.

Our detailed analysis, utilizing a comprehensive administrative dataset from the IIA spanning fourteen years, revealed that while R&D grants positively influence venture survival and the ability to secure follow-on funding, they do not uniformly lead to optimal financial outcomes. Specifically, our findings suggest that grants are more effective in environments characterized by significant financial frictions, such as at the top of the venture propensity score distribution, sectors and regions with low VC activity or high technological intensity. For example, our results indicate that grants are more effective when provided to ventures located in Jerusalem or the Western Negev region, where the availability of VC funds is low. However, this positive impact is often counterbalanced by instances of inefficient resource allocation, particularly in regions or sectors already flush with capital or lower in technological innovation. Consequently, our analysis indicates a crowding-out effect when providing grants to ventures located in Tel Aviv, unless they are at the forefront of R&D.

Similarly, we find that grants directed toward sectors with high R&D intensity and low VC funding are more likely to produce positive effects. In particular, ventures in the Communications and Miscellaneous sectors experience a substantial additionality effect, whereas those in IT & Enterprise and Life Sciences experience crowding out. As before, these results can be explained by the level of financial friction in each market, which is influenced by technological novelty and access to VC funds.

Our findings contribute to the literature by highlighting the substantial variation in the effects of R&D grant policies, which are closely tied to internal factors such as technological sectors and geographical domains. This variation suggests that the use of regression discontinuity (RD) designs, a common method in existing studies, might lead to biased evaluations of these programs. Similarly, analyses focusing solely on average effects risk overlooking crucial variations and may also yield biased outcomes. Our study underscores the importance of a nuanced examination of policy impacts across different scenarios and contexts. By adopting this comprehensive approach, policymakers can gain more detailed and useful feedback, enabling them to devise more precise funding strategies. Such strategic targeting of R&D subsidies could significantly enhance their effectiveness by concentrating resources in areas where they are most needed and where they have the potential to make the greatest impact.

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1.8 Tables and Figures

Table 1.1: Descriptive Statistics

	Non-Recipients		Recipients		Diff.	
Variable	Mean	SD	Mean	SD	df	p
Panel A: Observed covariates						
Req. Budget	4.30	3.05	4.70	3.16	-0.41	0.01
Review Score	2.91	0.61	3.73	0.43	-0.82	0.00
Raised VC_0	0.67	0.47	0.76	0.43	-0.09	0.00
$Sales_0$	0.08	0.27	0.08	0.27	-0.00	0.83
Ex-Ante $Round_0$	0.95	0.94	1.21	1.05	-0.26	0.00
VC $Amount_0$	1.88	6.09	3.22	10.16	-1.34	0.00
Panel B: Venture performance						
$Active_1$	0.99	0.11	0.99	0.12	0.00	0.91
$Active_2$	0.94	0.24	0.97	0.18	-0.03	0.01
$Active_3$	0.89	0.31	0.94	0.23	-0.05	0.00
Follow on_1	0.13	0.34	0.22	0.42	-0.09	0.00
Follow on_2	0.23	0.42	0.36	0.48	-0.13	0.00
Follow on_3	0.30	0.46	0.44	0.50	-0.14	0.00
VC $Amount_1$	2.67	10.71	4.33	11.07	-1.66	0.00
VC $Amount_2$	3.70	15.81	6.13	16.02	-2.42	0.00
VC $Amount_3$	5.60	26.04	8.27	20.36	-2.67	0.02
N	693		1177		1870	

Notes: This table provides summary statistics for grant applicants submitted to the IIA. Panel A displays the key observed covariates of pivotal grant applications, including the *Req. Budget*, which represents the requested R&D budget for the proposed projects in millions of New Israeli Shekels (ILS). The *Review Score* indicates the evaluation score given to each project by the IIA's technology review expert. *Raised* VC_0 is a dummy variable that equals one for ventures that have received VC financing prior to the IIA's grant decision date. Similarly, $Sales_0$ is a dummy variable that equals one for firms reaching the sales stage before the grant decision. The *Ex-Ante* $Round_0$ counts the number of funding rounds a venture has raised before the grant decision, and *VC* $Amount_0$ measures the millions of dollars raised from VC investors prior to the award decision. Panel B highlights the post-award performance statistics of the ventures. *Active* is a dummy variable that takes a value of one if a venture is still active in the respective year following the award decision. *Follow on* is a dummy variable that is assigned a value of one if the venture secures a subsequent funding round in the year following the award. Lastly, *VC Amount* measures the millions of dollars raised in subsequent funding rounds from VC investors.

Table 1.2: Logit regression results - first-stage propensity score matching

	Dependent variable:
	Grant Reception Indicator
Review Score	-6.175***
	(1.043)
Review Score^2	1.752***
	(0.181)
Ln(1+Req. Budget (million ILS))	-0.517***
	(0.184)
Venture's Age	-0.0787*
	(0.0403)
VC Amount (million dollars)	-0.0261*
	(0.0143)
Intercept	5.391**
	(2.714)
Sector*Year FE	Yes
Ex-Ante Round FE	Yes
Observations	1870
Log Likelihood	-556.1298
Pseudo R^2	0.5489

Notes: This table presents the results from the first stage propensity score matching, using a logit regression for estimating the likelihood of obtaining a grant. The dependent variable, *Grant Reception Indicator,* is binary and indicates whether an R&D grant was received. The list of controls include *Review Score*, and its square, the natural logarithm of the requested R&D budget in millions of Israeli Shekels (ILS), the age of the venture, and the amount of venture capital funding in million dollars. The coefficients provided express the log odds of receiving a grant. Fixed effects for Sector-Year and Ex-Ante Round are applied to adjust for temporal and round-specific variations, enhancing the model's robustness. Standard errors are reported in parentheses. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

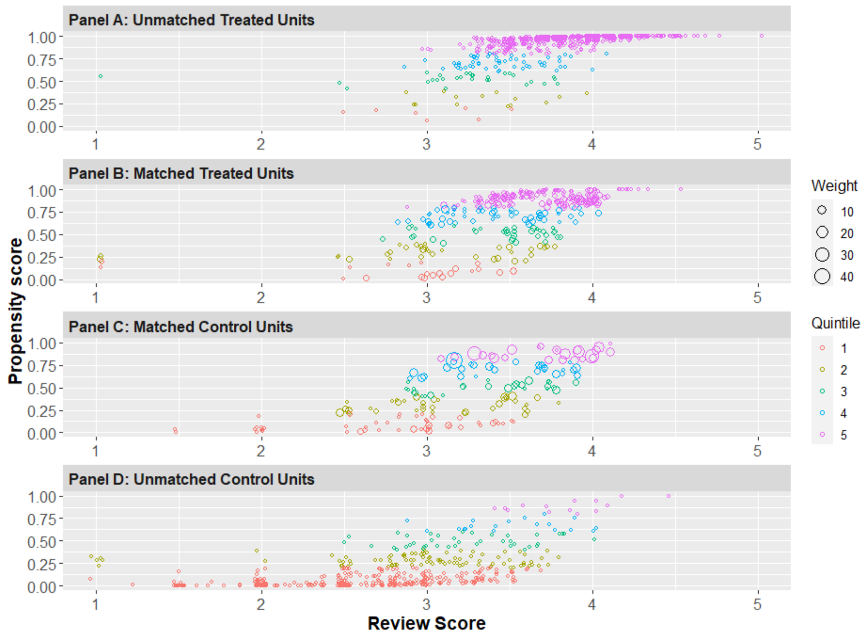
Figure 1.1: Joint Distribution of propensity scores and review scores

Panel A: joint-distribution, by award status

Panel B: joint-distribution, by program year

Notes: This figure shows the joint distribution of propensity scores and review scores. Panel A focuses on the distribution by award status, and Panel B by program year, illustrating variations across different categories and time.

Figure 1.2: Joint distribution of propensity scores and review scores by quintile and matching outcome

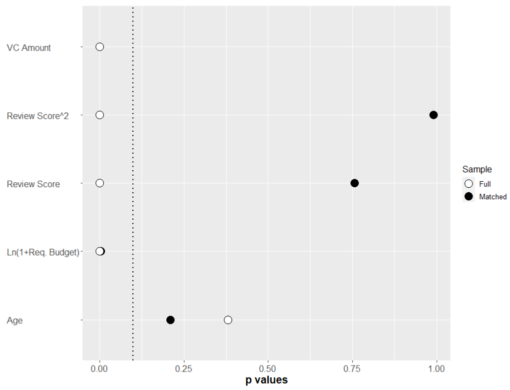


Notes: This figure illustrates the joint distribution of propensity scores and review scores segmented by quintile and matching outcome. *Weight* indicates the frequency with which a specific observation recurs in the sample. *Quintile* denotes the quintile number assigned based on propensity scores: scores below 20% fall into quintile 1, scores between 20-40% into quintile 2, and so on. Panel A displays unmatched treated units, Panel B shows matched treated units, Panel C features matched control units, and Panel D presents unmatched control units.

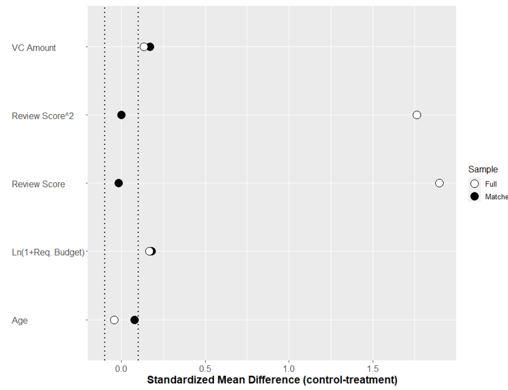
Figure 3: Assessment of Covariate Balance in the Propensity Score Matched Sample

Panel A: Quintiles 1 to 5

Panel A.1: p values

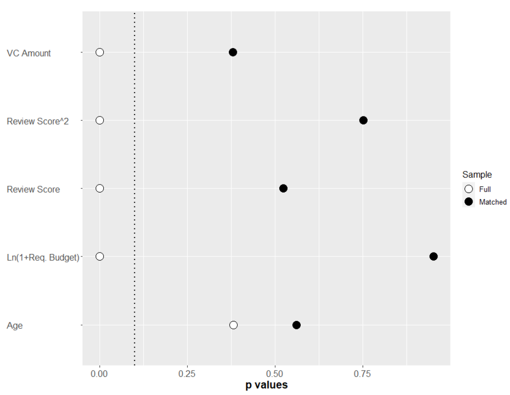


Panel A.2: Standardized mean difference

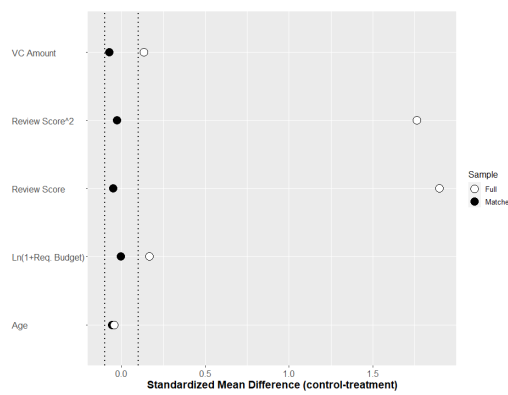


Panel B: Quintiles 2 to 4 (1 and 5 are excluded)

Panel B.1: p values



Panel B.2: Standardized mean difference



Notes: This figure presents the results from assessing covariate balance following the matching of awarded and non-awarded R&D projects using propensity scores. Panel A illustrates the results across the five quintiles. Panel A.1 displays the matching results for observed covariates used in the matching, using p-values. A covariate is considered balanced if the black dot (indicating the matched outcome) is positioned to the right of the dotted line. Panel A.2 shows the balancing results using the standardized mean difference as a test, where a balanced covariate is indicated by the black dot being positioned between two dotted lines. Panel B repeats the analysis from Panel A but focuses on quintiles 2 through 4.

Figure 4: Average venture characteristics, per quintile group

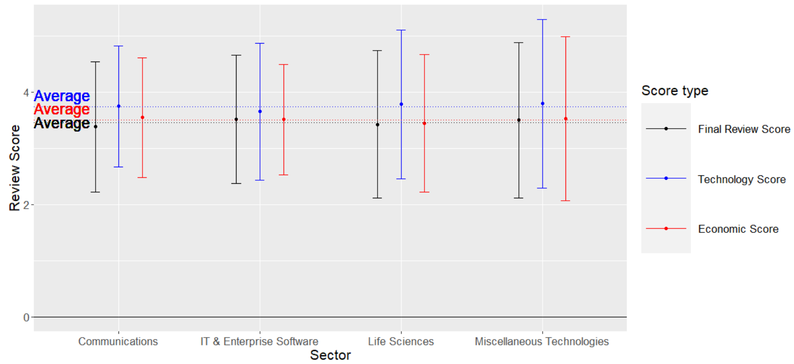
Panel A: Review Scores

Panel B: Sector Intensity

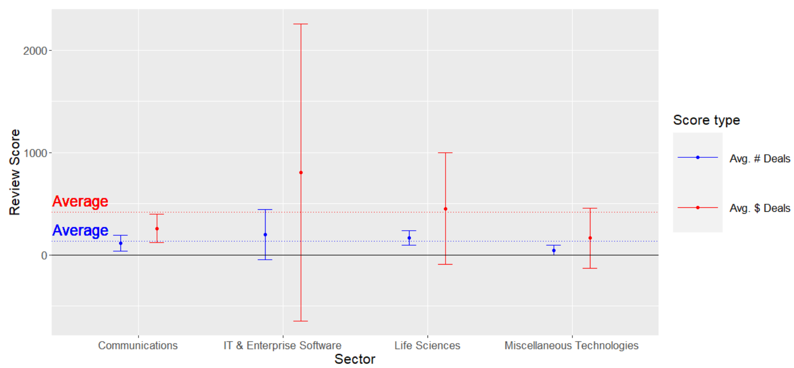
Notes: This figure displays average venture characteristics by quintile group. Panel A presents the average review scores from the IIA technology expert, including: (a) the final review score, and (b) the technology score, measuring the complexity and intensity of the R&D project, as well as (c) the economic score, assessing the potential economic impact on the Israeli economy in terms of employment, production, etc. Both the technology and economic scores are calculated based on a hand-collected sample of 415 projects that applied for support between 2006 and 2010. Panel B provides statistics on sector intensity, detailing the number of deals and their total amount in sectors associated with the ventures in each quintile.

Figure 5: Average venture characteristics, by sector affiliation

Panel A: Review Scores



Panel B: Sector Intensity



Notes: This figure illustrates average venture characteristics by sector. Panel A details average review scores from the IIA technology expert, which include: (a) the final review score, (b) the technology score—measuring the complexity and intensity of the R&D project, and (c) the economic score—assessing the potential impact on the Israeli economy in terms of employment and production. The technology and economic scores are based on a hand-collected sample of 415 projects that applied for support between 2006 and 2010. Panel B presents temporal averages of sector intensity, calculating the number of deals and their total value using the application year as the reference year.

Table 1.3: Matched Sample Overview

A. Sample Overview	Matched sample: Extended (1-5)	Matched sample: Narrow (2-4)	Non-matched
Observations	1094	484	1870
Observation (0.2<ps<0.8)	484	484	509
Unique Observations	384	207	1870

	Matched sample					
	Extended (1-5)		Narrow (2-4)		Non-matched	
B. Socioeconomic Priority Regions	N	Share (%)	N	Share (%)	N	Share (%)
G - Tel-Aviv and Central District	890	81.35	368	76.03	1474	78.82
A - Northern District	96	8.78	57	11.78	192	10.27
B - Jerusalem	82	7.50	47	9.71	155	8.29
O/T - Western Negev	26	2.38	12	2.48	49	2.03

	Matched sample					
	Extended (1-5)		Narrow (2-4)		Non-matched	
C. Industries	N	Share (%)	N	Share (%)	N	Share (%)
Communications	42	3.84	20	4.13	210	11.23
IT & Enterprise Software	354	32.6	148	30.58	412	22.03
Life Sciences	672	61.43	300	61.98	630	33.69
Miscellaneous Technologies	26	2.38	16	3.31	172	9.2
Other(s)	0	0	0	0	446	23.85

	Matched sample					
	Extended (1-5)		Narrow (2-4)		Non-matched	
D. P-score Quantiles	N	Share (%)	N	Share (%)	N	Share (%)
1 - 0<p-score≤ 0.2	84	7.68	0	0	413	22.08
2 - 0.2<p-score≤ 0.4	130	11.88	130	26.86	194	10.37
3 - 0.4<p-score≤ 0.6	142	12.98	142	29.34	146	7.80
4 - 0.6<p-score≤ 0.8	212	19.38	212	43.8	169	9.03
5 - 0.8<p-score≤ 1	526	48.08	0	0	948	50.69

Notes: This table offers a comparative overview of two matched samples: the extended sample, covering quintiles 1-5, and the narrow sample, which includes only quintiles 2-4. Additionally, information on the non-matched sample is provided for reference. Panel A details the number of observations in each sample, including those within the common support area (quintiles 2-4) and the count of unique observations. Panel B outlines the socioeconomic priority regions as designated by the Israeli government. It is important to note that these priority regions are not mutually exclusive; for example, a city in the central district might be categorized under priority regions A, B, O, or T, with each letter representing areas predominantly composed of municipalities that form the majority in their respective categories. Panel C describes the distribution of applications across various technology sectors, with "Other(s)" encompassing non-matched sectors as detailed in Appendix Table A1.4. Panel D illustrates the distribution of project applications across the propensity score quintiles.

Table 1.4: OLS results - impact of grant reception on ventures

	(1)	(2)	(3)	(4)	(5)	(6)
	Active_1	Active_3	Follow-On_1	Follow-On_3	VC Amount_1	VC Amount_3
Award Status=1	0.00506	0.0711***	0.0773***	0.0844***	0.0511	-0.976
	(0.00816)	(0.0177)	(0.0258)	(0.0320)	(0.252)	(1.349)
Review Score	-0.0217	-0.0661	-0.0750	0.0248	-2.303*	-9.404***
	(0.0201)	(0.0522)	(0.0947)	(0.106)	(1.175)	(3.331)
Review Score^2	0.00241	0.00839	0.0158	0.00863	0.382**	1.849***
	(0.00365)	(0.00855)	(0.0159)	(0.0177)	(0.186)	(0.544)
Ln(1+Req. Budget)	0.0117*	0.0139	0.0714***	0.0991***	1.070***	4.759***
	(0.00652)	(0.0139)	(0.0217)	(0.0257)	(0.411)	(1.514)
Age	-0.00188	-0.00121	-0.0198***	-0.0340***	-0.132***	-0.596***
	(0.00149)	(0.00274)	(0.00392)	(0.00488)	(0.0470)	(0.172)
VC Amount_0	0.0000626	-0.00275**	0.000412	0.00255	1.087***	1.455***
	(0.000162)	(0.00126)	(0.000978)	(0.00165)	(0.0487)	(0.182)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	No	No	No	No	No	No
Observations	1870	1870	1870	1870	1870	1870
R2	0.0574	0.0971	0.101	0.163	0.856	0.458

Notes: This table presents OLS coefficient estimates examining the impact of award decisions on venture performance, using the baseline (non-matched) sample described in Subsection 1.4.2. The analysis assesses three dependent variables measured one and three years after the award date: (1) Active—a dummy variable indicating whether a venture remains operational, (2) Follow-on—a dummy variable assigned a value of one for ventures that secured at least one private funding round in the year(s) following the award, and (3) VC Amount—a continuous measure of the US dollar amount (in millions) received from private funding rounds during the respective year(s) post-award. The regression includes baseline controls and fixed effects as outlined in Eq. 1.1. Standard errors are shown in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5: PSM results - impact of grant reception on ventures

	(1) Active$_1$	(2) Active$_3$	(3) Follow-On$_1$	(4) Follow-On$_3$	(5) VC Amount$_1$	(6) VC Amount$_3$
Award Status=1	-0.00212	0.0915***	0.100***	0.174***	-0.267	-6.331**
	(0.00572)	(0.0160)	(0.0273)	(0.0322)	(0.207)	(2.512)
Review Score	-0.452	-4.602***	-0.775	-0.483	-0.522	-11.88
	(0.315)	(0.621)	(0.644)	(0.803)	(3.939)	(26.73)
Review Score^2	0.128	1.315***	0.153	0.0821	-0.365	0.449
	(0.0892)	(0.176)	(0.173)	(0.224)	(1.087)	(7.610)
Ln(1+Req. Budget)	-0.0275	-0.335***	0.115*	0.166**	2.659***	20.64***
	(0.0298)	(0.0532)	(0.0630)	(0.0819)	(0.549)	(6.230)
Age	-0.00322	-0.0578***	-0.0170	-0.0263*	0.0263	-0.595
	(0.00507)	(0.00913)	(0.0109)	(0.0136)	(0.0642)	(0.407)
VC Amount$_0$	-0.000305	-0.00716*	-0.00708	0.0260**	0.965***	2.107***
	(0.00159)	(0.00417)	(0.00556)	(0.0114)	(0.0542)	(0.753)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1094	1094	1094	1094	1094	1094
R2	0.571	0.632	0.524	0.588	0.873	0.631

Notes: This table presents ATT coefficient estimates from a second-stage PSM regression, assessing the impact of award decisions on venture performance. The analysis utilizes the extended matched sample described in Subsection 1.5.2. Three dependent variables are evaluated one and three years post-award: (1) Active—a dummy variable indicating whether a venture is still operational, (2) Follow-on—a dummy variable that equals one for ventures securing at least one private funding round in the subsequent year(s), and (3) VC Amount—a continuous measure reporting the US dollar amount (in millions) received from private funding rounds during the respective year(s) after the award. The regression incorporates baseline controls and fixed effects as specified in Eq. 1.1 and an additional pair fixed-effect. Standard errors are shown in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.6: Heterogeneity analysis - the impact of a grant by prop. score quintiles

	(1) Active$_1$	(2) Active$_3$	(3) Follow-On$_1$	(4) Follow-On$_3$	(5) VC Amount$_1$	(6) VC Amount$_3$
1st Quintile ($\theta_0 + \theta_1$)	0.0072	0.1805***	-0.1396	0.0715	-1.6771**	-8.5485**
	(0.0206)	(0.0671)	(0.0861)	(0.1043)	(0.7863)	(3.8699)
2nd Quintile ($\theta_0 + \theta_2$)	0.0279*	0.0155	0.0381	-0.0321	-0.2909	-6.1628*
	(0.0154)	(0.0272)	(0.0865)	(0.0834)	(.6534)	(2.6369)
3rd Quintile ($\theta_0 + \theta_3$)	0.0114	0.0710**	0.0289	0.0480	-1.399*	-32.54***
	(0.0120)	(0.0312)	(0.0731)	(0.0865)	(0.820)	(12.16)
4th Quintile ($\theta_0 + \theta_4$)	-0.0171	-0.0193	0.0328	0.0268	0.3462	-2.9207*
	(0.0160)	(0.0286)	(0.0660)	(0.0717)	(0.2520)	(1.6633)
5th Quintile (θ_0)	-0.0110	0.1607***	0.2282***	0.3817***	0.1515	2.5347
	(0.0068)	(0.0302)	(0.0353)	(0.0430)	(0.2216)	(1.7957)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quintile FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1094	1094	1094	1094	1094	1094
R2	0.395	0.865	0.745	0.842	0.901	0.652

Notes: This table presents ATT coefficient estimates from a second-stage PSM regression, analyzing how award decisions influence venture performance across different quintiles. The coefficients aggregate the relevant treatment effects for each quintile, as outlined in Eq. 1.3. The analysis is based on the extended matched sample described in Subsection 1.5.2. Three dependent variables are evaluated one and three years after the award: (1) Active—a dummy variable that indicates whether a venture remains operational, (2) Follow-on—a dummy variable set to one for ventures that secured at least one private funding round in the subsequent year(s), and (3) VC Amount—a continuous measure of the US dollar amount (in millions) received from private funding rounds during the specified years post-award. The regression includes baseline controls and fixed effects as specified in Eq. 1.3. Standard errors are shown in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.7: Heterogeneity analysis - the impact of a grant across geographical locations

	Panel A: Extended matched sample - quintiles 1-5					
	(1)	(2)	(3)	(4)	(5)	(6)
	$Active_1$	$Active_3$	$Follow\text{-}On_1$	$Follow\text{-}On_3$	$VC\ Amount_1$	$VC\ Amount_3$
Tel-Aviv (θ_0)	-0.00567	0.0955***	0.102***	0.206***	-0.340	-7.774**
	(0.00573)	(0.0200)	(0.0323)	(0.0368)	(0.244)	(3.412)
Northern District ($\theta_0 + \theta_1$)	-0.0038	0.2154***	-0.0609	-0.1080	-0.6489	-4.3825
	(0.0128)	(0.0709)	(0.0915)	(0.1779)	(0.8233)	(4.1387)
Jerusalem ($\theta_0 + \theta_2$)	0.0249	-0.1835***	0.3304***	0.1636	0.8938	-0.1193
	(0.0279)	(0.0564)	(0.1163)	(0.1299)	(0.8828)	(3.8581)
Western Negev ($\theta_0 + \theta_3$)	0.1297	0.2881**	0.2145	0.2704	-0.2525	15.0475
	(0.1399)	(0.1446)	(0.2040)	(0.2122)	(1.3775)	(11.5347)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1094	1094	1094	1094	1094	1094
R2	0.586	0.644	0.533	0.592	0.876	0.634

	Panel B: Narrow matched sample - quintiles 2-4					
	(1)	(2)	(3)	(4)	(5)	(6)
	$Active_1$	$Active_3$	$Follow\text{-}On_1$	$Follow\text{-}On_3$	$VC\ Amount_1$	$VC\ Amount_3$
Tel-Aviv (θ_0)	-0.00426	0.0242	0.00448	0.00583	-0.860*	-19.80***
	(0.00723)	(0.0157)	(0.0546)	(0.0570)	(0.466)	(7.012)
Northern District ($\theta_0 + \theta_1$)	0.0111	0.0968**	-0.1719	-0.3354	-0.6800	-4.6760
	(0.0217)	(0.0462)	(0.1216)	(0.2434)	(0.7910)	(6.5668)
Jerusalem ($\theta_0 + \theta_2$)	0.0525	-0.1130**	0.5006***	0.0475	2.5600**	-4.0248
	(0.0339)	(0.0569)	(0.1683)	(0.1655)	(1.2455)	(9.5070)
Western Negev ($\theta_0 + \theta_3$)	0.9382***	0.4118	1.0971**	1.1727***	-0.4071	23.1618
	(0.0682)	(0.3439)	(0.5226)	(0.4226)	(2.0522)	(16.8276)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	484	484	484	484	484	484
R2	0.746	0.720	0.545	0.661	0.828	0.688

Notes: This table displays ATT coefficient estimates from a second-stage PSM regression, which assesses the impact of award decisions on venture performance across different socioeconomic priority regions. The coefficients summarize the treatment effects for each region as specified in Eq. 1.4. Panel A reports results using the extended matched sample, described in Subsection 1.5.2, while Panel B utilizes the narrow matched sample detailed in Subsection 1.5.3. Three dependent variables are analyzed one and three years post-award: (1) Active—a dummy variable indicating whether a venture remains operational, (2) Follow-on—a dummy variable assigned when ventures secure at least one private funding round in subsequent years, and (3) VC Amount—a continuous measure reporting the US dollar amount (in millions) received from private funding rounds during the designated years post-award. The regression incorporates baseline controls and fixed effects as outlined in Eq. 1.4. Standard errors are shown in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.8: Heterogeneity analysis - the impact of a grant by sector

	Panel A: Extended matched sample - quintiles 1-5					
	(1)	(2)	(3)	(4)	(5)	(6)
	Active_1	Active_3	Follow-On_1	Follow-On_3	VC Amount_1	VC Amount_3
Life Sciences (θ_0)	-0.0130**	0.0256	0.0501	0.110**	-0.419*	-4.072**
	(0.00531)	(0.0166)	(0.0360)	(0.0436)	(0.214)	(1.737)
Communications ($\theta_0 + \theta_1$)	0.168**	0.137	0.210***	0.190*	0.584	3.927
	(0.0656)	(0.0944)	(0.0667)	(0.108)	(0.434)	(3.329)
IT & Enterprise Software ($\theta_0 + \theta_2$)	-0.0114	0.170***	0.171***	0.288***	-0.0236	-10.54**
	(0.00747)	(0.0314)	(0.0429)	(0.0494)	(0.367)	(4.954)
Miscellaneous ($\theta_0 + \theta_3$)	0.0741	0.299**	-0.118	-0.243	-2.585	-11.90
	(0.0615)	(0.136)	(0.222)	(0.218)	(2.220)	(13.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1094	1094	1094	1094	1094	1094
R2	0.609	0.647	0.531	0.598	0.874	0.634

	Panel B: Narrow matched sample - quintiles 2-4					
	(1)	(2)	(3)	(4)	(5)	(6)
	Active_1	Active_3	Follow-On_1	Follow-On_3	VC Amount_1	VC Amount_3
Life Sciences (θ_0)	-0.00428	-0.00876	0.0371	-0.0315	0.112	-9.025**
	(0.00455)	(0.0119)	(0.0645)	(0.0727)	(0.348)	(3.799)
Communications ($\theta_0 + \theta_1$)	0.233**	0.208**	0.340***	0.1000	-0.222	-8.355
	(0.0945)	(0.0932)	(0.117)	(0.194)	(0.796)	(8.369)
IT & Enterprise Software ($\theta_0 + \theta_2$)	-0.0143	0.0362	-0.0315	-0.0553	-1.660**	-29.79***
	(0.0112)	(0.0260)	(0.0687)	(0.0617)	(0.726)	(9.983)
Miscellaneous ($\theta_0 + \theta_3$)	-0.0215	-0.00568	0.0562	-0.317	1.649*	20.86
	(0.0163)	(0.0194)	(0.0474)	(0.287)	(0.928)	(12.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ex-Ante Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	484	484	484	484	484	484
R2	0.726	0.710	0.527	0.650	0.828	0.694

Notes: This table presents ATT coefficient estimates from a second-stage PSM regression, assessing the impact of award decisions on venture performance across various technology sectors. The coefficients provide a summary of the treatment effects for each sector, as defined in Eq. 1.5. Panel A shows results from the extended matched sample, as described in Subsection 1.5.2, while Panel B features results from the narrow matched sample, detailed in Subsection 1.5.3. Three dependent variables are evaluated one and three years after the award: (1) Active—a dummy variable indicating whether a venture remains operational, (2) Follow-on—a dummy variable assigned to ventures that secured at least one private funding round in the following years, and (3) VC Amount—a continuous measure of the US dollar amount (in millions) received from private funding rounds during the specified years post-award. The regression includes baseline controls and fixed effects as specified in Eq. 1.5. Standard errors are shown in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.9 Appendix

Figure A1.1: Regional Characteristics

	(1) Ventures	(2) Investors	(3) R&D Centers
Tel Aviv	1600	83	93
Northern District	167	9	11
Jerusalem	113	9	1
Western Negev	45	1	3

Notes: This table presents information on regional characteristics, gathered from the online platform ”MappedinIsrael.com.” The ”Ventures” column lists the number of active ventures in each region. Similarly, the ”Investors” and ”Incubators” columns provide data on the number of active investors and incubators, respectively, in each region. Lastly, the ”R&D Centers” column indicates the number of active R&D centers in each region.

Table A1.2: Sector definitions by IVC (matched sectors)

IVC Sector	Definition
Communications	The Communications sector includes technologies that are targeted at the private and public telecommunications markets. It may be easier to define as what it does NOT include, such as Internet technologies, communications-related semiconductors and new media – all to be found under different sectors in the database. The technologies that ARE included are mainly related to communications infrastructures on the one hand and specific applications and devices on the other.
IT & Enterprise Software	This sector groups together various software sub-sectors, emphasizing the aspect of Information Technology (IT) systems for the Enterprise market. Companies developing software products for enterprises and for business end-users can be found here, as well as some companies developing software for the home market, including various software components for use in PCs – either by an individual end user, or by a business end-user. It should be noted however that the sector does not encompass all companies where software is the core technology, since companies with software targeted at specific market niches are sometimes more relevant for other Sectors. Such companies may be found under Internet, Life Sciences/Healthcare IT, Communications/Telecom Applications and Semiconductors/Manufacturing Equipment & EDA. Also, embedded software technologies and products are more likely to be found by the products' target market or function, in Cleantech, Communications, Semiconductors, Life Sciences and Miscellaneous Technologies.
Life Sciences	Life Sciences is a general term used to refer to biological technologies, medical technologies and healthcare-related technologies. Companies developing products for the healthcare market can be found in this sector, along with companies performing biological and genetic research, and companies developing technologies, tools and materials used in such research.
Miscellaneous Technologies	Other technologies not specified in Sectors above. These include: defense and homeland security technologies, hardware, industrial technologies, nanotechnologies and various other technologies that are not better described by one of our more defines sectors and sub sectors.

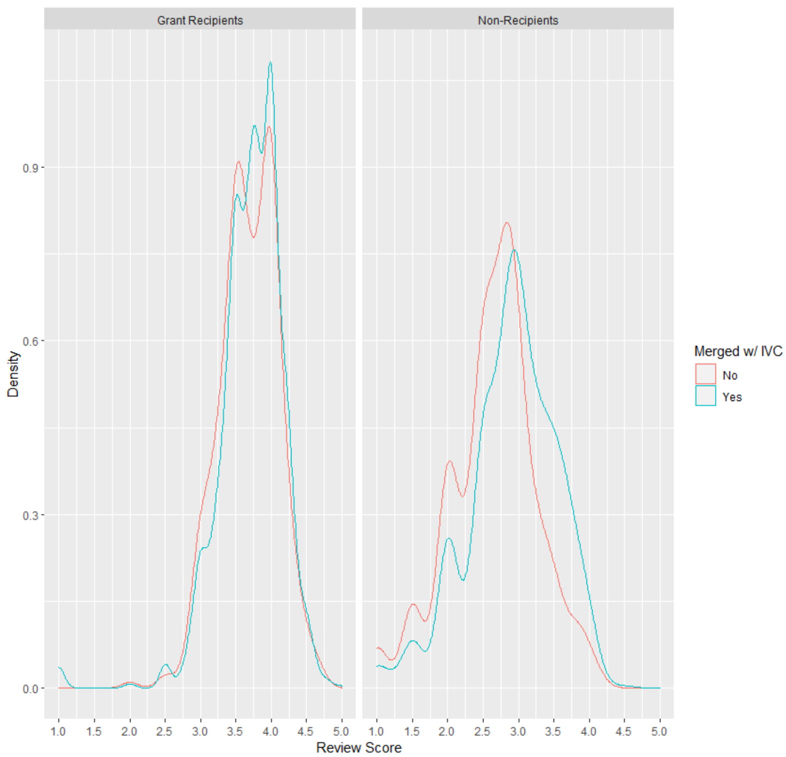
Notes: This table provides sectoral definitions as categorized by the IVC Research Center, specifically for sectors where our matching algorithm identified comparable matches (refer to Subsection 1.5.2). These definitions were sourced from the IVC website at https://www.ivc-online.com/Keyword-Glossary/High-Tech-Glossary. Additionally, due to changes in IVC's definitions over time, we used the Internet Archive ("https://web.archive.org/") to retrieve definitions as they were listed at the start of 2023, coinciding with our data collection period.

Table A1.3: Sector definitions by IVC (non-matched sectors)

IVC Sector	Definition
Agritech	Agritech, Agrotech, Agro Technology or Agricultural Technology, refers to the application of technology and innovation in the agricultural sector. AgriTech encompasses a wide range of technologies, including automation, biotechnology, artificial intelligence, big data analytics, and genetic engineering. These technologies are used in drones, robots, sensors, software systems, and crops to support functions such as field surveying and crop health monitoring, picking crops more efficiently and accurately, and reducing waste of resources like water and soil. Ultimately, the goal of AgriTech is to increase farm yields, reduce costs of production, improve the sustainability of farming, and increase the resilience of crops.
Cleantech	Short for Clean Technology, commonly used for products, services and processes designed to reduce or eliminate negative ecological impact and improve the productive and responsible use of natural resources. In this sector you will find companies developing eco-friendly technologies, technologies promoting efficiency and economy in the use of resources, recycling technologies and recyclable materials and technologies for the prevention and treatment of pollution.
Internet	The sector includes mostly companies developing software applications and services that are primarily used over the Internet, as well as technologies for the use of Internet Service Providers (ISP) and Internet users. Please Note that the basic communications infrastructures (hardware mostly) that create what is known as The Internet are to be found under the Communications sector, and the Networking, Optical Networking and Wireless Infrastructures sub-sectors in particular.
Semiconductors	Semiconductors devices are components that provide the memory, logic and intelligence functions in electronic systems. In this sector there are companies that develop semiconductors for various industries (fabless companies), manufacturer of chips (fabrication companies), develop the equipment for manufacturing the chips and develop software for the developers of the chips.

Notes: This table provides sectoral definitions as categorized by the IVC Research Center, specifically for sectors where our matching algorithm failed to identify comparable matches (refer to Subsection 1.5.2). These definitions were sourced from the IVC website at https://www.ivc-online.com/Keyword-Glossary/High-Tech-Glossary. Additionally, due to changes in IVC's definitions over time, we used the Internet Archive ("https://web.archive.org/") to retrieve definitions as they were listed at the start of 2023, coinciding with our data collection period.

Figure A1.1: Distribution of review scores by merge outcome and application award status



Notes: This figure illustrates the distribution of review scores, segmented by the outcome of merging the IIA and IVC datasets. The blue line represents project applications that were successfully merged with the IVC, while the red line indicates failures to merge the datasets. The overlapping density lines suggest that both merged and non-merged applicants are equally represented among both grant recipients and non-recipients.

Chapter 2

Deal Referrals and Fund Strategy in Venture Capital Networks

Deal Referrals and Fund Strategy in Venture-Capital Networks

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Abstract

Venture capital firms (VCFs) often refer investments to their network peers. Scholars argue that referrals alleviate idiosyncratic risks, and reduce the cost of sorting investments. Yet, research on the strategic implications of referrals on VCF is scant. The present study investigates the impact of network referrals on the redistribution of VCF resources within a referred deal and across other ventures in a VCF portfolio. At the deal-referral level, we hope to show that VCFs respond to the fall in idiosyncratic risks by increasing their financial exposure while reducing monitoring activity. As such, deal referrals allow VCFs to save resources while taking an advantageous financial position in the referred venture. We also aim to show that deal referrals motivate the redistribution of resources in a portfolio.

2.1 Introduction

Venture capital firms (VCF) form networks through investment syndicates. This collaborative approach constitutes approximately 70% of all VCF-backed deals in the US and 88% of all VCF-backed IPOs (Tian (2012)). Previous studies on VCF syndicates, starting with Bygrave (1988), have shown that co-investments facilitate the exchange of independent deal evaluations and complementary assets, reducing idiosyncratic risks (Bottazzi, Da Rin, and Hellmann (2016); Lerner (1994); Tian (2012)). Syndicates also play a crucial role in the diffusion of tacit information, extending beyond the boundaries of individual deals (Bygrave (1988); Granovetter (1985); Lerner (1994); Sorenson and Stuart (2001)). However, the impact of tacit information diffusion within syndicate networks on VCF strategy remains relatively unexplored.

We study whether, and if so, how, syndicate network referrals affect a VCF deal- and portfolio- strategy. This type of referral is of particular interest to the VC industry. Recent figures from a large VC survey indicate that network-referred deals account for 31% of an average VCF deal flow (Gompers, Gornall, Kaplan, and Strebulaev (2020)), and are associated with lower costs for searching, sorting, screening, and selecting investments (*"sorting costs"*)[1][2] (Wang (2016)). Drawing on the concept of social embeddedness, Burt (2002), argues that networks provide access to private information, allowing decision-makers to remove some ambiguity from their decisions. In the VC market, multiple studies report that direct and indirect network ties influence finance decisions (Batjargal (2007); Shane and Cable (2002); Shane and Stuart (2002)). Relatedly, Hochberg, Ljungqvist, and Lu (2007), provide empirical evidence that better-networked VCFs achieve higher returns on their portfolio.

Despite the prevalence of network-referred deals, their impact on a VCF strategy is relatively underexplored. There are two types of strategies undertaken by VCFs to enhance an investment's financial performance (Sørensen (2007)). First, VCFs carefully sort high-prospect ventures by leveraging their industry expertise, network access, and employing rigorous sorting processes (Amit, Brander, and Zott (1998); Edelman, Manolova, Brush, and Chow (2021); Gompers, Kovner, and Lerner (2009); Gompers et al. (2020); Petty, Gruber, and Harhoff (2023)). In the VC market, which is fraught with information problems between investors and founders, the ability to effectively sort high-potential investments becomes particularly pertinent (Hall and Lerner (2010); Hall and Woodward (2010); Kerr, Nanda, and Rhodes-Kropf (2014); Zacharakis and Shepherd (2007)). Hence, access to tacit information enables VCFs to improve operational efficiency. In particular, reliable tacit information on the quality of prospected ventures allows a VCF to distinguish promising ventures from less viable ones, reducing a deal's idiosyncratic risk. This relates to a wide range of evidence showing that VCFs leverage industry signals to mitigate information asymmetries in prospected ventures (Bernstein, Korteweg, and Laws (2017); Conti, Thursby, and Rothaermel (2013); Howell (2020)).

A second strategy pertains to the added value a VCF brings to its investments after sorting them. Specifically, a well-designed contract that details a deal's financial terms, along with the VCF's equity and control rights may fur-

[1] Gompers et al. (2020), denote that when sorting through investment opportunities, VCFs use a multi-stage selection process that is known as the deal funnel. Therefore, we consider sorting as a process that starts with generating a potential deal and ends with an investment.

[2] Gompers et al. (2020); Sørensen (2007)

ther reduce a deal's idiosyncratic risk, thereby enhancing overall investment performance (Kaplan and Stromberg (2001)). For instance, VCFs often stage their investments into small rounds with a clear set of goals and deadlines. This rigorous contracting allows VCFs to mitigate agency problems, obtain additional information before committing to larger rounds, and terminate underperforming projects early (Bergemann and Hege (2005); Gompers (1995); Tian (2011)). Consequently, the amount secured in a deal and a deal's stage in a venture's life cycle represent a focal risk tolerance, holding other factors constant. In addition, a well-designed contract may reduce a deal's risk by specifying the allocation of control rights.[3] Thus, a VCF may engage in active monitoring practices through the board of directors and reshape a venture's strategy (Bernstein, Giroud, and Townsend (2016); Bottazzi, Da Rin, and Hellmann (2008); Ewens and Marx (2018); Gerasymenko, De Clercq, and Sapienza (2015)).

Taking into account these interrelated derisking strategies, we examine how network referrals impact the redistribution of strategic resources within VCFs. We propose that "network-referral" effects become evident in VC markets characterized by costly information (Cumming and Zambelli (2017)), where VCFs may discover promising venture prospects through their network of syndicate peers. Notably, prior research by Wang (2016), suggests that ventures are more likely to be considered for an investment by a VCF with whom they share social ties. Moreover, Guenther, Özcan, and Sassmannshausen (2022), reports that referrals reduce due-diligence costs for VCFs, leading to better VCF-venture fit.

We assume a degree of substitution between dyadic match quality, a deal's financial structure and monitoring. This, we believe, is a reasonable assumption primarily given the scarcity of time as a VCF resource (Kirsch, Goldfarb, and Gera (2009); Petty and Gruber (2011)).[4]While the labor-intensive nature of sorting and monitoring implies that they can act as substitutes, the relationship becomes less apparent when we consider a deal's financial structure. However, it is essential to remember that a staging strategy is also labor-intensive, as it involves frequent assessments, due diligence, and contract designs. Thus, we hypothesize that referred deals are associated with increased financial exposure and a lower likelihood that a VCF would closely monitor an investment. Second, we hypothesize that the liberation of VCF resources from one venture in a portfolio increase resources devoted to peer portfolio ventures, thereby boosting a VCF's overall performance. Finally, provided that the degree of substitution increases with constraints over a VCF resources - we predict higher network-referral effects for resource-constrained VCFs.

This paper contributes to a growing literature on the effect of VCF syndicate networks. While prior studies have shed light on the significance of these networks in facilitating venture deals (Batjargal (2007); Gompers et al. (2020); Shane and Cable (2002); Shane and Stuart (2002); Stuart and Sorenson (2007)), there remains a limited understanding of their broader impact on a VCF strategy. In exploring this trajectory, we relate to the work of Sorenson and Stuart (2001) and Jääskeläinen and Maula (2014), who demonstrate that information diffusion within VCF networks facilitates investments in geographically distant locations. Similarly, we wish to show that information diffusion within VCF networks, specifically through deal referrals, allows VCFs to dynamically

[3]For comprehensive review, refer to Gompers and Lerner (2001) and Da Rin, Hellmann, and Puri (2013)

[4]The opportunity cost of an additional day spent on sorting an investment is one day less spent helping portfolio firms grow.

optimize their fund's resources.

We test our predictions in a consecutive venture setting, where VCF networks obtain tacit information on ventures founded by serial founders. To the best of our knowledge, this setting is most similar to Bengtsson (2013), which studies the benefits involved with multiple VCF-founder deals across different ventures. We follow Bengtsson's design to explore refereed investments in serial founders, who form a prominent subgroup of all VCF-backed founders (Gompers, Kovner, Lerner, and Scharfstein (2010)). This setting allows us to proxy network-referred deals, in which serial founders receive financing for a new venture from a VCF connected through a network peer (referee) to one of the same founders' previous ventures. Although we can not observe information transfers, we assume that private information flows to the VCF regardless of whether the referee initiated the transfer of information or has done so upon request.[5] By following this design, we are able to investigate whether indirect VCF-venture relations are associated with changes in a VCF's deal- and portfolio- strategy.

Our research setting provides several advantages for investigating our research question. First, we overcome the lack of referral data by focusing on serial founders. This approach allows us to examine situations where referrals are likely to occur, utilizing a thorough analysis of a founder's history and social ties. Despite the potential noise in this measure, we consider it the best available alternative, as it helps mitigate self-selection issues that might arise in survey-based research. Moreover, our study of serial founders contributes significantly to the limited literature on this topic, enhancing the overall significance of our research.[6] Secondly, among the myriad factors influencing investment decisions in ventures, the quality of the founding team stands out as the most crucial factor (Bernstein et al. (2017); Gladstone and Gladstone (2002); Gompers et al. (2020)). This perspective underscores the importance of early access to private information about the team's quality when making investment decisions. Indeed, our referral proxy aims to capture precisely this type of private information. By leveraging data on serial founders and their referral-based relationships with VCFs, we can gain valuable insights into the role of private information in venture capital investment decisions.

Our findings indicate that network referrals play a significant role in driving the reallocation of a VCF's resources within both the referred deal and across other ventures within the VCF's portfolio. At the deal level, our results demonstrate that VCFs respond to the reduction in sorting costs by enhancing their financial exposure. VCFs that possess social connections to founders through their syndicate network of VCF partners seem to expedite the process of entering new deals by approximately 10%, as compared to those lacking such social ties. Moreover, our analysis reveals a significant surge of 13% in the underlying round amounts for referred deals. This trend exhibits a consistent pattern across VCFs of varying sizes. Delving into the influence of deal referrals on monitoring behavior, our study unveils that these referrals are linked to a minimum reduction of 15% in the monitoring resources allocated to referred ventures. This pattern, however, is discernible primarily among small-traditional VCFs. This finding suggests that the informational value of a referral holds the most potency for

[5]We believe that is a strong assumption given the evidence that VCFs check, on average, eight references before making an investment decision (Gompers et al. (2020)).

[6]Gompers et al. (2010) emphasize that while serial founders constitute a significant group among VCF-backed founders, there is a relative scarcity of research specifically dedicated to studying serial founders in the VC literature.

financially constrained VCFs that strategically deploy resources to empower their portfolio firms.

Taking a portfolio perspective, we argue that sparing VCF resources, thanks to a deal referral from a trustworthy network peer, should allow a VCF to devote extra resources to other ventures in its portfolio. Indeed, our results find that portfolio ventures benefit from a 5% increase in the amount of monitoring resources allocated to them if a peer portfolio venture is referred. This result is robust to multiple sensitivity tests, meaning that VCFs are able to dynamically optimize their portfolio resources. Despite this result, we find no evidence that dynamically optimizing monitoring resources in a VCF portfolio increases the probability that portfolio firms will experience an exit event. However, this result might be driven by simplistic success proxies and changes in underlying risk preferences.

The rest of the paper is organized as follows: Section 2.2 outlines the hypotheses, Section 2.3 presents the data and research design, Section 2.4 elaborates on the empirical approach, Section 2.5 delivers the results, Section 2.6 wraps up with conclusions, and Section 2.7 delves into the limitations and potential directions for future research.

2.2 Hypotheses

To address our research question, we conduct a comprehensive two-part analysis. In the first part, we investigate how referrals influence the financial exposure and monitoring practices of VCFs. As mentioned earlier, having access to private information is believed to enhance the compatibility between the VCF and the venture, leading to a reduction in idiosyncratic risk. Drawing on previous research, we put forth the hypothesis that an improved alignment between a VCF and a venture increases the likelihood that a VCF would expedite its entry time into a deal while making a larger investment.

Access to a reliable referee plays a crucial role in mitigating uncertainties and ambiguities specific to each venture (Batjargal (2007); Burt (2002); Shane and Cable (2002); Shane and Stuart (2002)). As a result, VCFs can enhance their financial exposure to the venture. Our analysis measures financial exposure using two indicators: a VCF's entry time to an investment, reflecting the risks associated with high information asymmetries and the absence of tangible assets (Gompers and Lerner (2001); Hall and Lerner (2010); Hall and Woodward (2010)), and the amount invested by a VCF in its initial venture-level investment. While the latter serves as a direct measure of financial exposure, the former serves as a unique proxy, capturing the complexities faced by venture founders in establishing venture legitimacy (Fisher (2020); Zimmerman and Zeitz (2002)). Based on these measurements, we propose the following hypotheses:

H1.A.: Refereed deals are associated with larger financial exposure, as indicated by a shorter entry time.

H1.B.: Refereed deals are associated with larger financial exposure, as evidenced by larger investment amounts.

Furthermore, we anticipate that the impact of network referrals will be more pronounced for VCFs with limited resources, as the substitution between sorting quality, monitoring, and deal structuring may become more significant under resource constraints. To explore this further, we differentiate between three types of VCFs: micro, traditional small, and traditional large. This distinction arises from the observation that micro VCFs typically employ distinct investment strategies compared to their traditional counterparts (Pelucco, Amore, and Conti (2022)). Specifically, micro VCFs often invest smaller amounts in seed/pre-seed ventures and avoid taking active monitoring positions in the board. Therefore, despite their financial constraints, we do not expect to observe significant effects for micro VCFs.

In contrast to micro VCFs, small-traditional VCFs operate as financially constrained VCFs with a more comprehensive investment strategy. These small VCFs allocate investments across a range of amounts in both early and late-stage ventures, conduct rigorous due diligence, and actively monitor their investments through the board of directors. Given their broader investment scope and active monitoring practices, we anticipate that small-traditional VCFs will derive greater benefits from the presence of network referrals. The combination of their financial constraints and proactive approach to investment, may allow small-traditional VCFs to extract larger advantages from network referrals. Overall, the comprehensive investment strategy of small-traditional VCFs, coupled with their financial constraints, allows them to capitalize on the benefits offered by network referrals.

H1.1: Small-traditional VCFs will increase their financial exposure more than micro and large VCFs.

VCFs employ measures of organizational alignment to evaluate prospective ventures, which are evident in early interactions and the due diligence process (Bernstein et al. (2017); Cumming and Zambelli (2017); Howell (2020)). According to Gompers et al. (2020), VCFs typically evaluate around 100 potential investments per deal, requiring months of rigorous assessment before making an investment. This process incurs costs associated with gathering investee information and conducting background checks (Cumming and Zambelli (2017)). Considering the trade-off between sorting quality and monitoring, as observed in prior research (Kaplan and Stromberg (2001); Kirsch et al. (2009); Petty and Gruber (2011)), we hypothesize that refereed deals are associated with lower levels of venture monitoring. That is because referred deals reduce sorting costs and facilitate improved VCF-venture alignment. We measure monitoring with the number of positions held by a VCF on a venture's board of directors.

H2: Refereed deals are associated with lower levels of monitoring, as measured by the number of board seats occupied by a VCF.

H2.1: Small-traditional VCFs reduce venture monitoring, in a referred deal, more than micro and large VCFs.

In the second part of the analysis, we aim to examine the impact of deal referrals on a VCF portfolio strategy. A VCF trades off sorting and monitoring from a portfolio perspective. Therefore, the liberation of VCF resources from one venture should increase resources devoted to other ventures in a portfolio. The VC literature suggests that the marginal return on sorting is higher than the marginal return on monitoring (Gompers et al. (2020); Sørensen (2007)). Therefore, VCFs should devote spared resources to sorting new investments, up to the point where the marginal return from sorting is equal to the marginal return from monitoring. However, as per data limitations, we cannot observe the number of resources devoted to sorting tasks. Therefore, we focus on analyzing the impact of referred deals on fund-level monitoring. Hence, our third hypothesis posits that portfolio ventures whose peers have been referred *("network ventures")* will attract higher levels of monitoring resources compared to portfolio ventures whose peers haven't been referred *("non-network ventures")*.

H3: Network ventures are associated with higher levels of venture monitoring, as measured by the number of board seats occupied by their VCF, compared to non-network ventures.
H3.1: Network ventures of small VCFs are associated with higher levels of venture monitoring, compared to network ventures of micro and large VCFs

Hypothesis H3 states that deal referrals facilitate the redistribution of a fund's resources, such that, network portfolio ventures will attract higher levels of monitoring resources. A theoretical and empirical review of the VC/PE literature notes that board monitoring positively impacts financial performance (Bernstein et al. (2016); Bottazzi et al. (2008); Brav, Jiang, Ma, and Tian (2018); Ewens and Marx (2018)). Thus, our fourth hypothesis suggests that network portfolio ventures outperform non-network portfolio ventures. We proxy for portfolio venture performance with a successful exit dummy, that receives the value one if a venture went through an initial public offering (IPO) or- a merger/acquisition (M&A).

H4: Network portfolio ventures outperform non-network portfolio ventures, as proxied by their successful exit (IPO or an-M&A) history.
H4.1: Network portfolio ventures of small VCFs experience a larger performance increase, compared to network portfolio ventures of micro and large VCFs.

2.3 Data and design

2.3.1 Study Design

To investigate the influence of network-referred deals on a VCF fund strategy, we leverage data on venture deals sourced from Crunchbase. Crunchbase is a reputable commercial database that actively monitors the U.S. venture market since 2006. Using this data, we can connect VCFs to syndicate networks, which allows us to examine how network referrals impact VCF strategy.

Fig. 2.1 displays an illustration of our study design. We study the effect of network referrals in a consecutive venture setting. This enables us to observe VCFs' connections and thus explore how the presence of a potential referee affects VCF strategy. Let us consider a serial founder denoted as f, who has established two ventures: Venture A and Venture B. Venture A represents the initial venture founded by f, while Venture B denotes the subsequent one. Each venture has received funding from distinct VCFs, with j funded Venture A, and i funded Venture B. For the sake of simplicity, we employ the term "backer" to refer to any VCF associated with the first venture, and "investor" to denote VCFs linked to the consecutive venture.

We define an investor-backer pair as a network pair if they have previously formed a syndicate or if they have been jointly involved in a syndicate established by a third member. When an investor considers investing in a Venture B, they may gain access to tacit information about the founder's quality through their affiliations with backers, provided that a given investor-backer pair is also a network pair. In the presence of a network connection, we classify the backer as a "referee." Consequently, a unit of analysis composed of an investor-venture-founder triad can establish an indirect connection through a referee with whom the founder and the investor share direct social connections. In essence, within an investor-referee-venture-founder set, the referee is a backer who acts as a social bridge between the investor and the venture-founder pair.

<<Insert Figure 2.1 Here>>

Our empirical setting allows us to test how the existence of a referee affects VCF strategy. However, because of data limitations, we may not pin down the exact nature of information flows from a referee to an investor. That is because, data on the type of information transferred, the timing of exchange, or- the individual VCF associates facilitating it, is largely unreported by commercial data providers. However, given the vast evidence on information flows within VCF networks (Sorenson and Stuart, 2001; Batjargal (2007); Guenther et al. (2022); Hochberg et al. (2007); Shane and Cable (2002); Shane and Stuart (2002)), we cautiously assume the diffusion of tacit information and focus on how indirect social ties within VCF networks reshape a VCF strategy.

2.3.2 Serial founders and consecutive ventures

The sample of serial founders and consecutive ventures was collected using Crunchbase. First, we obtained a list of all U.S.-based founders who founded at least two ventures between 2006 and 2019. We conditioned the sample's start year on Crunchbase's establishment year to avoid a survival bias, while the end-year requirement allows us to observe at least three years of venture outcomes. Consequently, most first ventures are confined to the pre-2013 period, while most subsequent ventures were established after 2011. Second, as this study examines referrals through VCF networks, we limit our sample to serial founders who received VCF funding for their first and new ventures. This ensures that our analysis focuses exclusively on consecutive VCF-backed ventures founded by serial founders with ties to the VCF network. Thus, an indirect investor-venture connection could be drawn. Third, because data on fundraising amounts are occasionally unreported, we consider two samples - a main sample, which includes all relevant ventures, and an alternative, smaller sample, which provides extended fundraising data.[7]

Table 2.1 presents an overview of our sample's characteristics. As indicated in panel A, our main (alternative)

[7] In the appendix, we present the results from the alternative sample throughout the paper.

sample consists of 464 (373) serial founders who have received VC funding and who have founded 437 (342) consecutive ventures. These ventures were backed by 373 (326) different VCFs, resulting in 1143 (926) unique VCF-venture deals. Overall, our sample includes data on 1,342 (1,109) unique VCF-venture deals reported at the serial founder level.

<<Insert Table 2.1 Here>>

In Panel B, we present a distribution of the number of ventures founded by serial founders in our sample. The majority of founders (more than 82%) have founded exactly two ventures. Throughout this paper, we focus on consecutive ventures of serial founders. For example, a founder of two ventures has one consecutive venture that is considered for analysis. A founder of three ventures has two consecutive ventures (the second and the third), and so on.

Panel C provides information on the top five technological industries in which the ventures in our sample operate. Crunchbase reports a list of non-mutually exclusive affiliated industries per venture. Thus, we consider for each venture only the main industry reported by Crunchbase, out of 42 possible industries. Approximately a quarter of all ventures in our sample operate in the software industry, 11% in financial services and healthcare, 6% in commerce and shopping, 4% in transportation, and 46% operate in the remaining industries.

Panel D presents venture home-state distribution. The five most common states - California, New York, Texas, Washington, and Massachusetts, account for approximately 90% of all ventures in our sample. Notably, California and New York are home to 60% and 20% of the ventures, respectively, while Texas, Washington, and Massachusetts collectively account for 10%. The remaining 10% of ventures are distributed across other states.

2.3.3 Variable description

This subsection outlines the list of variables of interest, which will be detailed in subsection 2.3.4. While some of these variables will be incorporated into the empirical model as either dependent or independent variables, others are included to provide context and support the overall description.

Round Amount M$ is a continuous measure of the millions of dollars received in the first deal involving an investor with a venture. *Entry Round ID* is an ordinal categorical variable that assigns a number to the first financial round incorporating an investor-venture pair. Although these values have an inherent order (e.g., an investment in the pre-seed stage will be assigned a value of 1, seed stage will be 2, and round A will be 3), they do not represent a linear progression. This means the differences between each round do not correspond to a uniform or linear advancement of the venture. *Days to Announcement* is a continuous time variable that measures the number of days from the origination of the venture to the first deal involving the investor and the venture. *Number of Participating VCFs* is a count measure that indicates the number of VCFs involved in the syndicate for the first investor-venture deal. *Number of Board Seats* is a count measure indicating the number of the venture's board seats held by the VCF. *Number of Positions* refers to the number of positions within the venture occupied by the VCF. These positions include various board roles as well as other executive and non-executive level positions.

Successful Exit is a binary variable indicating whether the venture has undergone either an IPO or an M&A. This variable does not provide any information about the return obtained from the exit process.

The next set of variables pertains to the properties of the VCF itself, rather than the specifics of the deal. *Number of VCF Employees* is a count variable indicating the number of employees listed on Crunchbase. *Portfolio Size* is a count measure representing the number of ventures in the VCF's portfolio in the five years prior to the focal deal announcement date. *Network Centrality* measures the number of links held by each VCF in the network. *Network Betweenness* measures the importance of the VCF in the network by counting the number of times a VCF lies on the shortest path between other VCFs. *Network Eigenvector Centrality* is a measure of the influence of a node in a network, where the centrality of each VCF is determined not just by its own connections, but also by the centrality of the VCFs to which it is connected.

Founder-related variables include the following: *Successful Exit*, a binary variable indicating whether a founder has previously experienced a successful exit in a venture, defined as either an IPO or an M&A, without reflecting the return obtained through these processes. *IPO* is a binary variable indicating whether a founder's previous ventures included an IPO. *M&A* is a binary variable indicating whether a founder's previous ventures included an M&A. *Was a director at* V_j is a binary variable indicating whether a founder was a board member in one of their past ventures. *Is a director at* V_i is a binary variable indicating whether a founder is a board member in the focal venture.

The list also includes centrality measures of a founder's previous backers. *Maximum Centrality* represents the highest degree of centrality among the listed backers. *Maximum Betweenness* signifies the highest betweenness centrality among the listed backers. *Maximum Eigenvector* denotes the highest eigenvector centrality among the listed backers.

2.3.4 Descriptive statistics

Table 2.2 provides summary statistics for our sample of VC deals in consecutive ventures, differentiating between referred and non-referred deals. Referred deals are defined as analysis units where a focal VCF is indirectly connected to a focal venture-founder pair by a potential referee from the VCF's network of syndicate partners. In contrast, non-referred deals represent analysis units where there is no such connection. Out of our sample of 1342 VC-venture-founder deals, 766 are non-referred deals, while 566 are referred deals.

In Panel A, we present summary statistics for round- and deal-level properties and outcomes. The average round amount for both referred and non-referred deals is approximately $18.5 million, with no significant difference between the two groups. Similarly, the average entry round ID suggests that the representative investment is typically received in Round A. Investors of referred deals exhibit an average entry time to a deal of 710 days since venture inception, which is 142 days earlier than the average entry time of non-referred deals. This economically meaningful disparity supports the prevailing literature convention that deal referrals mitigate sorting costs and expedite the due diligence process. Moreover, referred deals involve an average of 4.59 participating VCFs, compared to 4.38 for non-referred deals. Although the economic impact is relatively small and statistically insignificant, this may also represent differences in investors' ability to acquire private tacit knowledge of a potential investee. Moving on to the analysis of monitoring resources, we find that the average VCF in our study dedicates 0.13 board members and employs approximately 0.22 VCF personnel who serve as board members, board observers, executives, or advisors. This highlights the significant role of VCFs in providing expertise and guidance to the ventures in which they invest. However, at the descriptive statistics level, we can't find any difference between the two groups.

In terms of deal-level success, we observe that, on average, 26% of referred deals and 22% of non-referred deals achieved a successful exit through either an IPO or an M&A transaction. Notably, these exit statistics appear to be slightly higher than the figures typically reported in VC studies.[8] However, it is important to recognize that these numbers are mechanically inflated due to the specific design of our study. Namely, our sample is structured at the VC-venture-founder level. Thus, each venture is represented multiple times, as a function of the number of investors and serial founders affiliated with it. This may introduce bias in the exit statistics, as more successful ventures are over-represented compared to unsuccessful ones. To provide a more accurate representation of the overall exit outcomes, we refer to Table A2.1, which organizes outcome statistics at the venture level. Panel A of this table reveals that 24% of the referred ventures[9] in our sample achieve a successful exit, compared to only 13% of the non-referred ventures. These averages are statistically different and better align with conventional levels of success.

Going back to Table 2.2, panel B provides summary statistics of VCF properties. We observe that VCFs with an indirect social connection to a venture are significantly larger in terms of employee count and portfolio size compared to their counterparts. Specifically, VCFs supporting referred ventures have an average of 26.6 employees, which is 9 employees more than their peers. Additionally, they have an average portfolio size of 49 ventures, while non-referred VCFs have an average of 34 ventures. Interestingly, despite these differences, there is no statistically significant variation in network centrality measures between the two groups.

Panel C presents founder-level and prior venture statistics. Founders of referred deals exhibited higher success rates in their previous ventures, with 60% of them successfully achieving an exit, compared to 50% of the non-referred group ($p<0.01$). This discrepancy in successful exit experience can be primarily attributed to differences in the share of founders that have experienced an M&A with their previous venture.[10] Furthermore, referred deals are associated with a greater number of founders holding director positions in the focal venture, while there is no statistically significant difference in terms of founders who held director positions in their previous venture.

Lastly, in panel D, we examine the maximum network centrality measures among a focal founder's previous backers. These measures allow us to mitigate the concern that our results are driven by a "certification" effect, where a reputable founder's backer passively signals to potential investors a focal founder's quality (Hsu (2004)).

[8] For instance, Rabi and Guzman (2020) reports that approximately 10-14% of Israeli ventures undergo either an IPO or an acquisition.
[9] Ventures with at least one referred deal
[10] refer to Table A2.1 for previous venture exit outcomes

We consider three network centrality measures - degree centrality, betweenness, and eigenvector. These measures assess the overall prominence of a backer within a network, where each backer represents a node in a larger network of syndicate partners. Degree centrality quantifies the number of direct connections a backer has with syndicate partners. Betweenness evaluates a backer's position in the shortest paths between syndicate partners, indicating their ability to control information or resource flow in the network. Lastly, eigenvector centrality determines a backer's prominence based on its direct connections and the prominence of the syndicate partners they are connected to, giving more weight to connections with other influential VCFs. The findings from panel D suggest that referred deals are associated with higher centrality measures among a founder's backers compared to non-referred deals. This may indicate that previous backers certify a founder's potential, regardless of the existence of a referral. To address this concern, we incorporate these centrality measures into our empirical model.

<<Insert Table 2.2 Here>>

2.4 Empirical approach

This paper seeks to evaluate the impact of deal referrals on a VCF deal and portfolio strategy. We suggest that referrals provide VCFs with valuable information for effectively sorting ventures, leading to increased financial exposure and reduced monitoring of referred ventures. From a portfolio perspective, this enables VCFs to optimize their allocation of resources across other ventures.

Despite the theoretical clarity of these network referral effects, accurately identifying their impact is complicated by the fact that referrals are not independent of a VCF, or- venture characteristics. Thus, simplistic estimations may be confounded by systematic biases in the data. A major concern arises when actual venture outcomes are correlated with a referral through the error term. In particular when ex-ante VCF's expectations about the venture are correlated with ex-post venture outcomes, which implies that a VCF can accurately evaluate venture outcomes in the absence of a referral.

$$Y_{ivf} = \alpha_0 + \theta_0 Referral_{ivf} + \beta_{1k} X_{ki} + \beta_{2m} X_{mvf} + FEs_q + \epsilon_{ivf} \tag{2.1}$$

We address these concerns in Equation 2.1, which presents our empirical model. Y_{ivf} represents the focal investor-venture-founder deal's outcome variable of interest. The variables of interest are as follows: ln(Entry Time), which denotes the natural logarithm of the time elapsed between venture inception and the opening round with a focal investor; ln(Round Amount), which represents the natural logarithm of the million dollars secured in the opening round at the investor-venture level; and the number of board seats occupied by an investor in a venture. The subscripts ivf respectively indicate the investor, venture, and founder. α_0 is the constant, $Referral_{ivf}$ is an indicator variable that takes the value of one if there exists an indirect first-degree social connection between the investor and the venture's founder through the VCF network - i.e., the focal investor has co-invested with at least one of the focal founder's backers. The coefficient of interest, θ_0, reflects a percentage point change in logarithmic outcome variables or an absolute change in non-logarithmic outcome variables.

We incorporate various controls and fixed effects in our regression model to mitigate endogenity. X_{ki} denotes a list of k controls at the investor level. These controls encompass logarithmic measures of deal-level syndicate size, investor's portfolio size, median entry time to new investments, the median amount invested in new portfolio ventures, network eigenvector centrality, and age. As such we are able to capture important aspects of an investor's resources, experience, specialization in early-/late-stage investments, and prominence within the network.

Furthermore, X_{mvf} represents a list of m controls at the venture-founder level. We consider founder-level experience by incorporating indicators for a serial founder's (un-)successful exit history, whether the founder served as a director in their previous venture, and whether the founder holds a director position in the focal venture. Additionally, we account for whether a referee who previously backed a focal founder was a lead backer, and whether the previous and focal ventures operate in the same technological industry. These controls should provide a signal for a referral's quality. Lastly, we consider the maximum level of eigenvector centrality associated with all of a focal founder's previous backers. The inclusion of this variable helps us address concerns regarding potential "certification" effects, rather than network referral effects.[11]

To mitigate remaining endogeneity concerns, we incorporate q fixed effects (FEs_q) for the venture's main technological industry and inception year, the deal's round ID, the focal founder's number of consecutive ventures, and investor ID. Finally, ϵ_{ivf} denotes the error term in the model. Since our analysis units are organized at the investor-venture-founder level, we cluster our regressions at the venture-founder level to address any potential issues arising from correlated errors at this level. This clustering helps ensure the robustness of our results.

Although we take steps to mitigate endogeneity concerns in our empirical approach, it is crucial to recognize that completely eliminating these concerns is a challenging task in the absence of a reliable instrumental variable. Yet, the presence of a random variation that directly influences referrals but lacks a direct impact on a VCF strategy raises doubts.

There are a few key reasons why exogenous variation in the assignment of referrals to VCFs may not effectively establish a causal claim, especially when private information is omitted from the analysis. That's because the inherent value of a referral is closely tied to its social context. Essentially, a referral is valuable only if it comes from a trustworthy peer. Therefore, a completely random assignment of referrals to VCFs would dilute the social context that gives the referral its significance.

We may assume, however, that while referrals are not distributed randomly, they are affected by an exogenous disruption in the VCF network communication. A priori, such a disruption might seem like a valid instrument, impacting the distribution of referrals to VCFs without influencing a VCF's portfolio strategy. However, two considerations suggest this approach is unlikely to meet both conditions simultaneously. First, given the extensive due diligence process in the venture capital industry, short-term disruptions would likely encourage patience as long as the referral maintains a positive expected value. Second, in cases of long-term disruption where patience

[11] Our results are robust to the inclusion of competing centrality measures.

is not feasible, it is reasonable to assume that the disruption would affect the VCF strategy as a whole. Therefore, in the absence of unobserved private information, an instrumental variable strategy would offer limited value. Consequently, without such an instrument, it is essential to exercise caution when interpreting our findings, as they cannot be solely attributed to causal referral effects.

2.5 Results

This section presents the empirical findings derived from evaluating the relationship between deal referrals and an investor's deal- and fund- strategy. Section 2.5.1 focuses on the connection between a deal referral and the corresponding deal-level strategy. Specifically, we investigate whether an investor, who's indirectly socially connected to a venture-founder pair through a first-degree network connection, intensifies its financial exposure to a referred venture-founder pair. We anticipate observing a positive association between referrals and an increased financial exposure to the venture-founder pair. Furthermore, we explore whether referrals exhibit a negative correlation with the allocation of monitoring resources at the deal level. Section 2.5.2 delves into how investors with a referral in their portfolio modify their portfolio strategy and assesses the impact on portfolio performance. We hypothesize that the release of investor resources from the referred venture would lead to a reallocation of resources towards other ventures within the portfolio, ultimately influencing portfolio performance.[12]

2.5.1 Referrals and deal-level strategy

The regression results for hypotheses H.1A and H.1B, are presented in panels A and B, respectively, of Table 2.3. Each panel consists of three specifications. In column (1), the results are based on Eq. 2.1, where a control for the maximum eigenvector centrality associated with a serial founder's previous backers and investor FEs are omitted. Column (2) excludes only investor FEs. Finally, our preferred specification in column (3) includes all controls and fixed effects as outlined in Eq. 2.1.

We test in panel A an investor's financial exposure to a deal by the natural logarithm of entry time, representing the number of days elapsed between a venture's inception date and the deal's announcement. To the extent that a referral reduces an investment's idiosyncratic risk, we expect a focal investor to increase its financial exposure to a deal. The study of entrepreneurial finance proclaims that early-stage ventures tend to be riskier compared to later-stage counterparts. Therefore, an expected increase in an investor's risk exposure could translate into an earlier entry time into a deal.

<<Insert Table 2.3 Here>>

The results from this panel provide empirical support for the notion that deal referrals have a significant impact on an investor's financial exposure to a venture, as measured by the number of days elapsed from venture inception to the announcement of a deal. In column (1), it is observed that investors who have a social connection

[12] Please refer to the corresponding section for a detailed discussion of the hypotheses.

to a venture-founder pair through the VCF network experience a 16.9% reduction in entry time. This result is statistically significant at the 1% level. To address the "certification" hypothesis, which suggests that investors assess the quality of a venture-founder pair based on the prominence of the founder's previous backers, Column (2) includes a control for the maximum eigenvector centrality associated with a focal founder's backers. The coefficient of interest remains economically strong (-16.3%) and statistically significant at the 1% level. In Column (3), investor fixed effects are incorporated to account for investor heterogeneity. Despite this inclusion, the coefficient of interest remains substantial, indicating a reduced entry time of 11.2% ($p<0.01$). We repeat these analyses in the corresponding panel of Table A2.2, over a constrained sample which excludes observations with missing funding amounts. Yet, we report consistent results across all three specifications, suggesting that investors accept higher levels of risk in referred deals.

Panel B examines hypothesis H1B, which considers an investor's financial exposure to a deal, measured by the natural logarithm of the round amount in millions of US dollars. To deal with the problem of non-reported funding amounts, we assume that deals with missing funding information are of small size. Thus, panel B reports regression results where we replace missing values with zeros.

The data in columns (1) - (2) of the panel indicate a correlation between referred deals and an increase in opening rounds amounts. However, these coefficients do not reach statistical significance based on conventional standards ($p > 0.1$). Nonetheless, when we consider investor fixed effects in column (3), the coefficient of interest demonstrates a significant ($p < 0.1$) 13.6% increase in opening round amounts. We verify this result in the corresponding panel of Table A2.2, which focuses on a sample of venture deals for which funding information is available. The results presented in this panel exhibit improved statistical robustness and reveal an additional 2 p.p increase in the amount invested in referred deals. Specifically, in column (3), we find that deal referrals are associated with a total 15.3% increase in opening round amounts ($p<5\%$). This evidence strongly suggests that investors increase their financial exposure to referred deals through early entry and larger monetary involvement.

<<Insert Table 2.4 Here>>

Next, we delve into hypothesis H1.1, which explores the influence of investor resource heterogeneity on the referral effects presented in Tables 2.3. Our objective is to determine whether network referral effects are more pronounced for resource-constrained investors, assuming that the marginal information value of a referral is higher for these investors. To classify investors based on their level of resource constraints, we assign them to three groups according to the number of employees working for the investor at the time of the opening investment announcement date. The first group, referred to as "micro", consists of investors in the bottom third of the distribution, which includes those with fewer than 6 employees. The second group, labeled as "small", encompasses those in the middle third of the distribution, with 6 to 16 employees. The benchmark group comprises investors in the top third of the distribution, with more than 16 employees. By examining the differential effects of referrals among these investor types, we can gain insights into the role of resource constraints in shaping the referral dynamics within the VCF network.

We reshape Equation 2.1 to account for investor heterogeneity. The refined model is represented by Equation 2.2, which includes additional terms to capture the impact on different investor types. Specifically, α_1 serves as the additive intercept for micro investors, α_2 represents the additive intercept for small investors, θ_1 denotes the interaction effect of a referral obtained by micro investors, and θ_2 signifies the interaction effect of a referral obtained by small investors. These additions allow us to explore the nuanced effects of investor heterogeneity in our analysis.

$$\begin{aligned} Y_{ivf} &= \alpha_0 + \alpha_1 Micro_{iv} + \alpha_2 Small_{iv} + \theta_0 Ref_{ivf} + \theta_1 Ref_{ivf} \times Micro_{iv} \\ &+ \theta_2 Ref_{ivf} \times Small_{iv} + \beta_{1k} X_{ki} + \beta_{2m} X_{mvf} + FEs_q + \epsilon_{ivf} \end{aligned} \tag{2.2}$$

As discussed in the section on hypotheses development, the number of resources possessed by an investor is correlated with its specialization in either the early or late stages of investments. Micro investors tend to specialize in the earliest stages, while large traditional investors specialize in more advanced stages, typically entering investments at round B or later. Traditional-small investors fall in between these two extremes. Consequently, for our analysis of an investor's entry time into an investment, we expect the following intercept order: $0 \geq \alpha_2 \geq \alpha_1$. Similarly, as investment size is associated with a round type, we anticipate similar intercept patterns in the analysis related to the investment amounts. Regarding our coefficients of interest, denoted as θ_1 for micro investors and θ_2 for small investors, we expect θ_1 to partially offset the baseline effect represented by θ_0. This expectation arises from the limited degrees of freedom micro-investors have in reshaping their strategy. That is because micro-investors leverage their scarce financial and human capital resources by entering early into investments. Conversely, for small-traditional investors, we anticipate θ_2 to intensify the baseline effect due to their greater flexibility in terms of entry time and investment amounts, while still needing to optimize their strategy within resource constraints. Therefore, we anticipate θ_2 to be negative for the analysis of entry time to an investment and positive for the analysis of investment amount.

The findings for both analyses are presented in Table 2.4. Panel A showcases the results pertaining to investor entry time, while panel B displays the results regarding investment amount. To ensure consistency, we utilize the alternative sample (N=1109) for both analyses, as it is more relevant specifically for the analysis concerning the invested round amounts. However, it is worth noting that the results for the first analysis exhibit a similar magnitude when considering the larger sample size (N=1342). Panel A demonstrates a significant intensification of the baseline effect, with an approximate decrease of 2-3 p.p, resulting in the following values across the three specifications: (1) θ_0 = -0.191, t_0 = 0.0552; (2) θ_0 = -0.186, t_0 = 0.0556; (3) θ_0 = -0.141, t_0 = -0.0565. Importantly, the statistical significance remains strong, with a p-value below 0.01 in columns (1) and (2) and a p-value below 0.05 in column (3). This result further supports our findings that deal referrals have an impact on investors' entry time. Yet, when considering the heterogeneous effects, both the additive intercepts, α_1 and α_2, as well as the interaction coefficients, θ_1 and θ_2, yield statistically insignificant results in columns (1) and (2). In column (3), which includes investor fixed effects, we observe additive intercepts of -24.3% ($p<0.1$) and -22.9% ($p<0.05$) for micro and small investors, respectively. These findings confirm our earlier expectations that investors' specialization in stages is correlated with the number of resources possessed by an investor. Nevertheless, based on the results in column (3), we find no evidence to support the presence of heterogeneous deal referrals effects, as both θ_1 and θ_2 are statistically indifferent from zero.

In panel B of Table 2.4, we investigate the effect on deal amounts, differentiating between micro, small, and large investors. The baseline effects in columns (1) to (3) are 13.2%, 13.2%, and 21.4%, respectively, reflecting a minimum increase of 4.5 p.p compared to those reported in Table 2.3. Furthermore, the additive intercepts α_1 and α_2 are statistically insignificant across all specifications, indicating that investors with more human resources typically do not participate in larger funding rounds, all else equal. The coefficient of interest, θ_1, represents the interaction between micro investors and deal referrals. Notably, in columns (1) to (3), θ_1 exhibits additive effects of -13.6%, -13.6%, and -22.6%, respectively. However, only the coefficient obtained from column (3) is significant at a conventional level ($p<0.05$). This outcome confirms our initial conjecture that θ_1 partially offsets the baseline effect captured by θ_0, suggesting that micro investors do not increase their investment amounts when they have a referral. Importantly, when combining θ_1 with θ_0, we find null effects: (1) θ_{1+0} = -0.003, t_{1+0} = -0.05; (2) θ_{1+0} = -0.003, t_{1+0} = -0.05; (3) θ_{1+0} = -0.011, t_{1+0} = -0.13. Examining the coefficient of interest, θ_2, which represents the interaction between small investors and deal referrals, we find null effects across all three specifications. This finding contradicts our initial conjecture that small investment firms would exhibit a greater increase in their opening round amounts compared to large investment firms.

<<Insert Table 2.5 Here>>

Thus far, our analysis has revealed that deal referrals are linked to a greater financial exposure of investors in referred ventures. Specifically, investors who have a first-degree indirect connection to a venture tend to enter the initial investment phase earlier and increase their financial contribution. These findings align with the notion that deal referrals help mitigate idiosyncratic risks associated with investments, enabling investors to expand their financial exposure. However, our findings do not support the hypothesis that the marginal value of a referral is higher for investors facing greater constraints. Instead, our results indicate that both traditional small and large VCFs respond similarly to referrals.

Next, we shift our focus to examine hypothesis H2, which suggests that the information value of a deal referral is a substitute for monitoring resources allocated by investors to a venture. We operationalize monitoring resources as the number of board seats occupied by an investor in a venture. The results of this analysis are presented in panel A of Table 2.5. These results indicate that the effect of a referral on the number of board seats is statistically and economically insignificant. In other words, our analysis does not detect any meaningful impact of deal referrals on the allocation of board seats by investors.

We employ Eq. 2.2 to address hypothesis H2.1, which proposes that the monitoring resources utilized by an investor in a venture depend on the interaction between a referral and the resource constraints of a VCF. Similar to our previous approach, we approximate a VCF's constraint by considering the number of employees working for a specific investor, distinguishing between large, small, and micro VCFs. The assignment of an employee to monitor a venture through the board is contingent upon the VCF's resources, hence the number of employees working for an investor serves as a suitable proxy for the investor's resource constraints. Consequently, we deduce the following additive intercept patterns: $0 \geq \alpha_2 \geq \alpha_1$. We anticipate that α_1, the additive intercept for micro VCFs, will be negative and smaller than α_2 due to the typical lack of monitoring activities by micro VCFs. We expect α_2 to be either negative or insignificantly different from zero, as smaller VCFs encounter greater constraints compared to large VCFs. In relation to this, we anticipate that θ_1, the additive coefficient representing the interaction between a referral and micro VCFs, will not deviate significantly from zero. Additionally, we expect θ_2, the additive coefficient capturing the interaction between a referral and small VCFs, to be negative. This expectation stems from the understanding that small VCFs generally engage in monitoring activities, and thus a referral should facilitate these VCFs in optimizing their resources.

Panel B of Table 2.5 presents the results obtained from the heterogeneity analysis of the effect of a referral on monitoring. Consistent with our expectations, the additive intercept α_1 in columns (1) and (2) is approximately -0.16, demonstrating statistical significance at the 1% level. Similarly, the additive intercept α_2 in both columns is around -0.06, yet is insignificantly different than zero. These results validate our prior expectations that the allocation of monitoring resources to a venture is influenced by the size of the VCF. Column (3) provides further support for this pattern, although both intercepts are statistically indifferent from zero. Moving on to the coefficients of interest, the baseline coefficients θ_0 in columns (1) to (3) do not exhibit significant deviations from zero at conventional levels of significance. Moreover, these coefficients hold little economic significance, as $\theta_0 \leq 0.0183$ across the three specifications. Consistent with our expectations, the coefficient of interest θ_1, representing the interaction effect between a referral and micro VCFs, does not show any significant deviations from zero. Lastly, we observe that the coefficient of interest θ_2, which captures the interaction effect of a referral obtained by a small VCF, is negative and statistically significant across all three specifications: (1) -0.135^{**}, (2) -0.133^{**}, and (3) -0.115^{*}. We test the sensitivity of these results to the chosen sample in Table A2.3, where we replicate the analysis using a constrained sample that excludes observations with missing funding amounts. Yet, we find that our results are robust, indicating that small VCFs decrease the allocation of monitoring resources to ventures for whom they obtain a referral. This finding underscores the notion that referrals enable small VCFs to optimize their resource allocation strategies.

2.5.2 Referrals and fund-level strategy

Thus far, our analysis has demonstrated that VCFs accept higher risk in their investments for which they obtain a referral. The results indicate that VCFs increase their financial exposure to ventures with whom they share a social connection through various means, such as rapid entry, larger financial rounds, and reduced monitoring. These referral effects can be attributed to the substitutive nature of the different strategies employed by VCFs when de-risking a deal. Consequently, a cost reduction in a single de-risking strategy, namely - sorting investments, has an effect on the likelihood that a substitute strategy will be deployed. Further, this should enable a profit-optimizing VCF to reallocate resources across its portfolio. As a result, a non-referred venture within a VCF's portfolio that includes a referred venture *("network portfolio's venture")*, may capture a larger portion of a VCF's resources.

This subsection aims to investigate two aspects: whether *network portfolio ventures* receive a higher proportion of resources from a VCF and whether these ventures demonstrate improved exit outcomes compared to their counterparts. To empirically define a portfolio, we follow two steps. Firstly, we consider a focal consecutive venture deal consisting of an investor (i), venture (v), and founder (f). Within this unit, we include investors who have made a minimum of ten new investments in the 5-year period before and after ivf's announcement date. This criterion ensures that we focus on investors actively managing a portfolio of ventures rather than those with only a couple of investments. Secondly, we examine the five investments made by an investor (i) that are closest to ivf's announcement date. This approach allows us to analyze the effect on ventures that are more likely to be influenced by the inclusion of a referred deal in the portfolio. In later stages, this would enable us to conduct a placebo test where we analyze the effect on random deals from an underlying portfolio, rather than the five closest ones. By following these steps, we obtain a sample of 5705 portfolio ventures. Among these, 3316 units are non-network portfolio ventures (control group), while 2389 are network portfolio ventures (treatment group).

$<<$Insert Table 2.6 Here$>>$

Panel A of table 2.6 presents deal-level descriptive statistics for our sample of portfolio ventures. The average deal amount for non-network portfolio ventures is \$20.37 million, while network portfolio ventures have an average deal amount of \$22.49 million. Although there is a notable difference of \$2.1 million, this gap is statistically insignificant. Both types of ventures received their initial investment from the focal investor at around round A. The average entry time of an investor into a non-network portfolio deal is 1078 days, which is 67 days more than the average entry time of an investor into a network portfolio deal. The number of participating investors differs significantly between the two groups, with an average of 3.9 investors participating in non-network portfolio ventures and 4.3 investors in network portfolio ventures. Furthermore, the average deal announcement time difference between a portfolio venture and an underlying consecutive venture is 76 days for non-network portfolio ventures and 31 days for network portfolio ventures. These figures demonstrate that the sample of portfolio ventures is comparable to the underlying sample of consecutive ventures, which is an important consideration since investors are more likely to reallocate resources across similar ventures. Next, we examine the number of board seats or venture positions occupied by a VCF - we find that network ventures are associated with 0.17 VCF's board members, compared to 0.15 in the non-network group. In panel B we examine success factors that are associated with portfolio ventures. Network portfolio ventures demonstrate improved exit outcomes, with 25% of them achieving a successful exit compared to only 21% of the non-network portfolio ventures. This statistically significant difference in exit outcomes is primarily driven by their prospects in the M&A market. These success measures also align with the size of the ventures, as we report that network portfolio ventures are on average 35% larger compared to their counterparts, with an average of 394 employees compared to 292 employees in the control group.

<<Insert Table 2.7 Here>>

Table 2.7 presents regression results for hypotheses H3 in columns (1) and (2) and H3.1 in columns (3) and (4). Hypothesis H3 suggests that portfolio ventures attract larger monitoring resources from their VCF when a peer portfolio venture is referred. Furthermore, hypothesis H3.1 proposes that these portfolio referral effects are more pronounced among small VCFs compared to micro and large VCFs. This expectation is based on the understanding that small VCFs actively engage in monitoring but face resource constraints, whereas micro VCFs typically do not engage in monitoring, and large VCFs engage in monitoring but are not as resource-constrained. Panel A of the table displays regression results based on the underlying main sample of consecutive ventures from section 2.3. In this analysis, a portfolio venture, k, represents a portfolio peer of a consecutive venture, i. The regression model includes baseline controls and a control variable for the logarithm of the number of syndicate partners backing a portfolio venture k. Additionally, we incorporate baseline fixed effects and fixed effects at the peer venture level, including fixed effects for k's deal year, sector, and round. To account for potential correlation within clusters, we cluster the analysis at the peer venture and investor levels. By including these controls and fixed effects, we aim to capture the specific dynamics and relationships within the sample, enhancing the reliability of our results.

The results from columns (1) and (2) of Table 2.7, demonstrate that peer portfolio ventures receive enhanced monitoring resources from a VCF when an affiliated consecutive venture is referred. This effect is both economically and statistically significant at the 95% confidence level. On average, portfolio ventures affiliated with a referred venture are assigned 0.059 more board members by their VCF, compared to portfolio ventures without an affiliation to a referred venture. Moving to columns (3) and (4), we examine the impact of investor heterogeneity. Interestingly, the baseline effect remains robust, whereas the coefficient of interest θ_1 and θ_2 are statistically equal to zero.

In Table A2.4, we perform a similar analysis, considering only portfolio ventures that are affiliated with an underlying consecutive venture from our alternative sample, as presented in section 2.3. Remarkably, the baseline coefficient θ_0 experiences an increase of about 2 p.p across all four specifications while remaining statistically significant. However, the additive coefficients θ_1 and θ_2 are statistically indistinguishable from zero. These findings support our conjecture that deal referrals motivate the redistribution of monitoring resources across ventures in a VCF's portfolio. However, hypothesis H3.1, which claims that resource-constrained investors, namely - small traditional VCFs, benefit the most from these referrals, is not supported by our findings and requires additional investigation.

To address concerns regarding the influence of unobserved investor characteristics on our results, we have implemented a placebo test, which is presented in Table A2.5. This test involves examining the impact of fund-level referrals on a randomly selected group of portfolio ventures, regardless of their specific deal timing. Thus, instead of focusing on the five nearest portfolio investments to a consecutive venture, we have randomly selected five different portfolio investments within the five-year timeframe preceding or following the investment in the affiliated consecutive venture. This approach serves as a relevant placebo test because it assumes that ventures financed in different investment cycles are unlikely to compete for the same resources. By conducting this placebo analysis, we can assess the level of bias in the results previously presented. It provides us with a baseline against which we can compare the actual effects of fund-level referrals, helping to establish the true impact of these referrals on the outcomes observed.

The results from the placebo test give confidence to our findings. Notably, both the baseline coefficient, θ_0, and the coefficient of interest, θ_2, which represents the interaction effect of a portfolio referral with small traditional VCF, diminish in terms of their economic magnitude and statistical significance. suggesting that portfolio ventures attract greater monitoring resources from a VCF when a peer portfolio venture is referred. In other words, when a referral is obtained for at least one venture, VCFs exhibit a tendency to redistribute their monitoring resources across the portfolio. This indicates a strategic allocation of resources driven by the presence of referrals, further reinforcing the significance of venture capital networks in influencing resource allocation within a VCF's portfolio.

<<Insert Table 2.8 Here>>

In order to complete our analysis, we investigate the correlation between deal referrals and the performance of peer portfolio ventures. By examining how deal referrals impact the performance of a VCF's peer portfolio ventures, we can gain valuable insights into networking dynamics, deal-sorting strategies, de-risking strategies, and the overall performance of the portfolio. This information can assist VCFs in making informed investment decisions, ultimately enhancing their financial performance.

To accurately assess the relationship between deal referrals and peers' performance, it is necessary to obtain information on the return on investment (ROI) associated with each venture in a VCF's portfolio. However, VCFs generally do not report this information to commercial databases. Moreover, due to the unique structure of VC funds as fixed-term limited partnerships, information regarding investment returns is typically disclosed to limited partners only at the end of the fund's life cycle, making it unavailable for analysis. To address this issue, we employ a successful exit dummy variable as a proxy for a venture's performance outcome. This variable is an indicator that takes the value of one whenever a portfolio venture is reported in Crunchbase to have experienced an exit, either through an IPO or a M&A.

Table 2.8 presents the regression results for hypotheses H4 and H4.1. In columns (1) and (2), we analyze hypothesis H4, which explores the impact of a deal referral on the performance of peer portfolio ventures. Columns (3) and (4) display the results for hypothesis H4.1, examining the interaction between variations in investor heterogeneity and the effects of deal referrals. Additionally, we present two panels. Panel A corresponds to portfolio ventures associated with the main sample of consecutive peer ventures, while panel B focuses on a subsample of portfolio ventures associated with consecutive ventures for which we have obtained complete funding information.

The results presented in table 2.8 challenge our earlier expectations and contradict the existing literature (Hochberg et al. (2007)), which emphasizes the role of networks in enhancing a VCF's performance. Surprisingly, there is no evidence to suggest that referrals have a positive impact on performance. This finding is particularly intriguing in light of our previous evidence demonstrating that VCFs strategically reallocate their resources in response to referrals. However, it is important to acknowledge a major limitation in our study, which may have influenced these results. Specifically, our use of a dummy variable for a successful exit as a proxy for success, rather than a continuous measure such as return on investment, could potentially bias these results downward. This limitation should be taken into account when interpreting these findings.

2.6 Conclusions

We study the unexplored impact of network referrals within VCFs on their deal- and portfolio-level strategies. VCFs form networks through investment syndicates, a collaborative approach that constitutes a significant share of VCF-backed deals and IPOs in the United States. Previous research has established that co-investments among VCFs facilitate the exchange of valuable deal evaluations and complementary assets, reducing idiosyncratic risks. However, the broader implications of tacit information diffusion within these syndicate networks on VCF strategies remain relatively unexplored.

Through an in-depth exploration, we demonstrated how network referrals influence the allocation of strategic resources within VCFs. Our findings reveal that network-referred deals have a significant impact, both at the deal level and within the broader portfolio. Specifically, VCFs respond to the efficiency gains attributed to referrals by increasing their financial exposure to referred deals. Additionally, VCFs with social connections to founders within their syndicate networks expedite their entry into new deals, showcasing an approximate 10% advantage compared to those without such ties. Furthermore, we observe a notable 13% increase in the underlying round amounts for referred deals, a trend consistent across VCFs of different sizes.

Taking a portfolio perspective, we highlighted the ripple effect of referrals on VCF strategies. Network-referred deals enable VCFs to reallocate resources, resulting in an increase in monitoring resources allocated to portfolio ventures with peer referrals. Despite these dynamic resource shifts, we did not find evidence supporting the notion that optimized monitoring resources translate to increased exit probabilities for portfolio ventures.

In the broader context of the VC landscape, our research adds depth to the understanding of VCF syndicate networks. While previous studies have underscored the significance of these networks in facilitating venture deals, our work delves into their intricate impact on VCF strategies. By investigating network referrals and their ramifications, we contribute to the emerging body of literature that explores how VCF networks go beyond deal facilitation, actively influencing strategy optimization.

This study bears relevance beyond its academic scope. Venture capital firms operate in an environment of information asymmetry, and access to tacit information can be a key differentiator. Our findings offer insights into how well-connected VCFs leverage referrals to optimize their decision-making processes and resource allocation, potentially leading to enhanced operational efficiency and investment performance.

To conclude, this study bridges a gap in understanding the influence of network referrals on VCF strategies, shedding light on how these referrals shape the allocation of resources and decision-making.

2.7 Limitations

While this study provides valuable insights into the impact of network referrals on VCF's strategies, there are certain limitations that warrant consideration. These limitations open up avenues for future research, exploring deeper aspects of the relationships and dynamics discussed.

One key limitation lies in the challenge of establishing causal relationships definitively. To establish a causal link between network referrals and VCF strategies, a random variation in the allocation of referrals would be necessary. Controlled or natural experiments could provide a more robust foundation for making causal claims. Future research might explore such experimental designs to strengthen the causal interpretation of our findings.

A second limitation pertains to the intricate mechanisms behind information flows. While our study highlights the influence of network referrals, it doesn't pinpoint the exact nature of information transmission. Understanding which types of information or agents are most effective in facilitating resource reallocation within VCFs remains an intriguing avenue for future investigation. Qualitative research or in-depth interviews could offer a more nuanced understanding of the information-sharing dynamics.

Lastly, our study's focus is centered on relational financing within the specific context of consecutive ventures. While this examination illuminates the significance of network referrals, it's important to recognize that relational financing can extend to a variety of other scenarios. Future research endeavors could delve into relational financing across different settings, particularly those where referrals are observed with minimal error. Broadening the investigation to encompass diverse contexts will undoubtedly enhance the generalizability of our findings. However, we acknowledge that pursuing such research might entail considerable data collection efforts. Commercial data providers are unable to provide information pertinent to this type of analysis. Nonetheless, the potential insights gained from exploring diverse settings would greatly enrich our understanding of the complex interplay between network referrals and the dynamics of venture capital strategies.

In conclusion, while our study has advanced the understanding of the influence of network referrals on VCF strategies, these limitations underscore the need for further exploration. Future research endeavors that address these limitations have the potential to offer more comprehensive insights into the complex interplay between network referrals and VCF decision-making processes.

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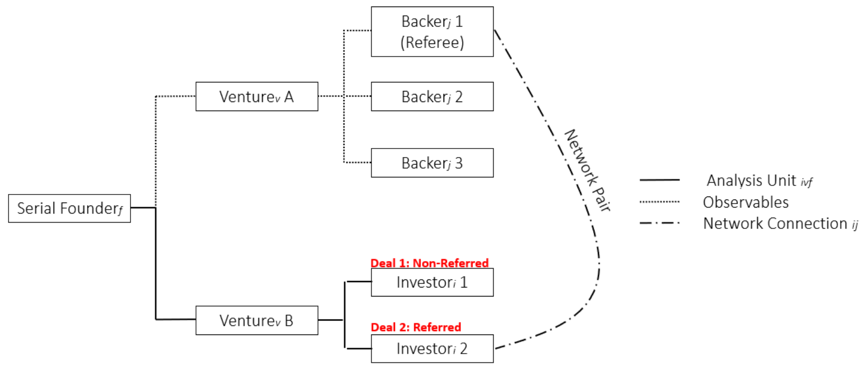
2.8 Tables and Figures

Figure 2.1: Illustration of study design



Notes: This figure illustrates the study's design as outlined in Section 2.3. $Venture_A$ represents the initial venture established by a serial founder, while $Venture_B$ denotes his subsequent venture. *Backers* are venture capital investors who supported the founder's first venture, whereas *Investors* finance the subsequent venture. The diagram depicts a social connection between $Backer_{i1}$ and $Investor_{i2}$ within the VCF network. This connection enables $Backer_{i1}$ to convey tacit knowledge about the founder to $Investor_{i2}$.

Table 2.1: Sample overview

A. Sample Overview	Main Sample		Alternative Sample	
Observations (VC-venture-founder)	1342		1109	
Number of unique VC-venture interactions	1143		926	
Number of unique VCs	373		326	
Number of unique consecutive ventures	437		342	
Number of serial founders	464		373	
	Main Sample		Alternative Sample	
B. Number of ventures for serial founders	N	Cum. Share (%)	N	Cum. Share (%)
2	381	82	302	81
3	55	94	45	93
4	23	99	21	99
5	5	100	5	100
	Main Sample		Alternative Sample	
C. Top 5 Industries	N	Cum. Share (%)	N	Cum. Share (%)
Software	293	22	260	23
Financial Services	154	33	119	34
Health Care	147	44	118	45
Commerce and Shopping	74	50	66	51
Transportation	74	54	63	56
Other(s)	600	100	483	100
	Main Sample		Alternative Sample	
D. Top 5 States	N	Cum. Share (%)	N	Cum. Share (%)
CA	791	59	679	61
NY	273	79	222	81
TX	50	83	40	85
WA	44	86	40	89
MA	35	89	26	91
Other(s)	149	100	102	100

Notes: This table provides a concise overview of the dataset. Panel A reports the number of observations for each sample under consideration. Panel B details the distribution of ventures founded by serial entrepreneurs within the sample. Panel C outlines the primary technological industries in which the sampled ventures operate, highlighting the top five sectors. Panel D depicts the geographic distribution of the ventures based on the home state of each.

Table 2.2: Deal-level statistics

	Non-Referred Deals		Referred Deals		Diff.	
Variable	Mean	SD	Mean	SD	df	p
Panel A: Deal Properties and Outcomes						
Round Amount M$	18.50	34.27	18.71	32.81	-0.20	0.92
Entry Round ID	2.95	1.38	2.98	1.32	-0.02	0.77
Days to Announcement	852.02	447.41	710.04	412.88	141.97	0.00
N. of Participating VCFs	4.38	2.76	4.59	2.86	-0.20	0.19
N. of Board Seats	0.13	0.35	0.13	0.38	-0.01	0.76
N. of Venture Positions	0.19	0.46	0.22	0.55	-0.04	0.21
Successful Exit (IPO/M&A)	0.22	0.42	0.26	0.44	-0.04	0.12
Panel B: VCF Properties						
N. of VCF Employees	18.05	24.96	26.60	35.25	-8.55	0.00
Portfolio Size	34.33	50.83	49.47	51.34	-15.14	0.00
Net. Centrality	13.43	24.03	13.80	21.67	-0.37	0.77
Net. Betweenness	1168.50	4185.14	1171.64	2971.03	-3.14	0.99
Net Eigenvec Centrality	0.06	0.10	0.06	0.10	-0.01	0.36
Panel C: Founder and Prior Startup Properties						
Successful Exit	0.50	0.50	0.61	0.49	-0.11	0.00
IPO	0.00	0.06	0.01	0.08	-0.00	0.44
M&A	0.50	0.50	0.61	0.49	-0.11	0.00
Was a Director at V_j	0.03	0.16	0.04	0.19	-0.01	0.31
Is a Director at V_i	0.06	0.23	0.08	0.28	-0.03	0.07
Panel D: Network Centrality Measures of Previous Backers - $Venture_j$						
Max. Centrality	162.53	108.21	195.77	109.98	-33.24	0.00
Max. Betweenness	47546.62	77589.79	62607.81	87957.82	-15061.20	0.00
Max. Eigenvector	0.56	0.23	0.66	0.19	-0.10	0.00
N^{notes}	766		566			

Notes: This table shows summary statistics at the unit of analysis level. Panel A displays deal properties and outcome measures. *Round Amount M$* is the total funds raised in a round that incorporates a focal deal. This measure is calculated using an N of 1109, with 635 non-referred and 474 referred. This inconsistency in N is due to missing reported amounts in Crunchbase. *Entry Round ID* is a factor variable that assigns a numerical value to each round type, as follows: {Pre-Seed=1, Seed=2, Round A=3,...}. *Days to Announcement* is the number of days between a startup's inception and a focal deal. *N. Part. Investors* returns a focal syndicate size. *N. Board Seats/Positions* return a count of seats/positions occupied by the VC, respectively. All exit statistics are based on dummy measures. Panel B displays VC statistics. *N. of VCF Employees* counts the number of VC employees. *Portfolio Size* returns the number of active investments in a VCF's portfolio. All centrality measures are based on a VC's network of syndicate partners. Panel C displays outcome measures of a founder's previous venture. Directorship measures are dummies for whether a focal founder was/is a director in his previous/focal startup, respectively. Panel D displays network centrality measures of the most centralized VCF who backed the focal founder in his previous startup.

Table 2.3: The effect of deal referrals on a VCF's financial exposure (H1)

	Panel A: Ln(Time-to-Announcement)			Panel B: Ln(Deal Amount)		
	(1)	(2)	(3)	(1)	(2)	(3)
Referral=1	-0.169***	-0.167***	-0.111***	0.0770	0.0870	0.136*
	(0.0495)	(0.0496)	(0.0385)	(0.0695)	(0.0698)	(0.0746)
Controls$_{(k+m)}$	Y	Y	Y	Y	Y	Y
FEs$_{(q-1)}$	Y	Y	Y	Y	Y	Y
Investor FEs			Y			Y
Observations	1342	1342	1342	1342	1342	1342
R2	0.420	0.420	0.768	0.717	0.717	0.836

Notes: This table reports OLS coefficients for effect of a referral on a VCF's financial exposure. We measure financial exposure in Panel A using the logarithm of the number of days passed from venture inception to deal announcement. In Panel B, financial exposure is proxied using the logarithm of the deal amount in millions of USD. The analysis is conducted at the investor-venture-founder level, with baseline controls and venture fixed effects included in all specifications. Column (3) additionally includes Investor FE. *Referral* is an indicator of an indirect connection between a $Investor_i$ and a founder through a network peer ($Backer_b$). Controls include indicators for a founder board membership (current and previous), previous venture success, previous venture cessation, referee's lead investor status, a founder's experience in a focal technology sector, deal syndicate size, an investor's portfolio size, an investor's median first engagement time with portfolio ventures, an investor's median amount invested in opening rounds, and an investor's eigenvector centrality. Fixed effects are included for a venture inception year, tech-sector, financing round, and founder to control for unobserved heterogeneity at these levels. Standard errors (in parentheses) are clustered by V_i and by $Founder$. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: The effect of deal referrals on financial exposure by investor's fund size (H1.1)

	Panel A: Ln(Days to Announcement)			Panel B: Ln(Deal Amount)		
	(1)	(2)	(3)	(1)	(2)	(3)
Referral=1	-0.191***	-0.186***	-0.141**	0.132*	0.132*	0.214***
	(0.0552)	(0.0556)	(0.0565)	(0.0738)	(0.0744)	(0.0784)
Micro VC=1	0.0691	0.0640	-0.243*	-0.0316	-0.0315	0.0128
	(0.0520)	(0.0526)	(0.147)	(0.0748)	(0.0749)	(0.210)
Referral=1 $\times$ Micro VC=1	0.0546	0.0540	0.0523	-0.136	-0.136	-0.226**
	(0.0657)	(0.0656)	(0.0702)	(0.0858)	(0.0859)	(0.103)
Small VC=1	0.0217	0.0180	-0.229**	-0.0836	-0.0834	-0.140
	(0.0498)	(0.0509)	(0.101)	(0.0646)	(0.0642)	(0.152)
Referral=1 $\times$ Small VC=1	0.0757	0.0796	0.0879	0.0476	0.0475	-0.0196
	(0.0835)	(0.0839)	(0.0776)	(0.110)	(0.109)	(0.116)
Controls$_{(k+m)}$	Y	Y	Y	Y	Y	Y
FEs$_{(q-1)}$	Y	Y	Y	Y	Y	Y
Investor FEs			Y			Y
Observations	1109	1109	1109	1109	1109	1109
R2	0.482	0.483	0.794	0.765	0.765	0.881

Notes: This table displays OLS coefficients analyzing the heterogeneous effects of referrals on a VCF's financial exposure, categorized by VCF size as defined in Eq. 2.2. Financial exposure is measured in Panel A using the logarithm of the number of days from venture inception to deal announcement, and in Panel B using the logarithm of the deal amount in millions of USD. The analysis is conducted at the investor-venture-founder level, with baseline controls and venture fixed effects included in all specifications. Column (3) additionally includes Investor FE. *Referral* is an indicator of an indirect connection between a $Investor_i$ and a founder through a network peer ($Backer_b$). Standard errors (in parentheses) are clustered by V_i and by $Founder$. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: The effect of deal referrals on monitoring (N. of board seats)

	Panel A: Hypothesis 2			Panel B: Hypothesis 2.1		
	(1)	(2)	(3)	(1)	(2)	(3)
Referral=1	-0.0276	-0.0198	-0.0119	0.0130	0.0183	0.00245
	(0.0260)	(0.0270)	(0.0307)	(0.0483)	(0.0487)	(0.0525)
Micro VC=1				-0.159***	-0.163***	-0.0653
				(0.0361)	(0.0361)	(0.105)
Referral=1 × Micro VC=1				-0.00751	-0.00443	0.0433
				(0.0489)	(0.0487)	(0.0544)
Small VC=1				-0.0611	-0.0629	-0.0460
				(0.0410)	(0.0413)	(0.0818)
Referral=1 × Small VC=1				-0.134**	-0.127**	-0.113*
				(0.0536)	(0.0536)	(0.0615)
Controls$_{(k+m-1)}$	Y	Y	Y	Y	Y	Y
FEs$_{(q-1)}$	Y	Y	Y	Y	Y	Y
Investor FEs			Y			Y
Observations	1342	1342	1342	1342	1342	1342
R2	0.146	0.148	0.550	0.174	0.176	0.555

This table presents OLS coefficients analyzing the effects of referrals on monitoring, as indicated by the number of board seats assigned to the VCF. Panel A examines the average effect, while Panel B explores the heterogeneous effects, categorized by VCF size as defined in Eq. 2.2. The analysis is conducted at the investor-venture-founder level, with baseline controls and venture fixed effects included in all specifications. Column (3) additionally includes Investor FE. *Referral* is an indicator of an indirect connection between a $Investor_i$ and a founder through a network peer ($Backer_b$). Standard errors (in parentheses) are clustered by V_i and by $Founder$. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Summary of deal-level statistics for sampled portfolio ventures

	Non-Network Ventures		Network Ventures		Diff.	
Variable	Mean	SD	Mean	SD	df	p
Panel A: deal properties and outcomes						
Deal Amount M$	20.37	51.97	22.49	65.80	-2.12	0.25
Entry Round ID	2.89	1.41	2.90	1.35	-0.01	0.85
Time to Entry	1078.59	979.80	1010.98	914.82	67.61	0.01
N. of Participating VCs	3.91	2.77	4.31	2.80	-0.39	0.00
Announcement Time Difference$_{ik}$ (Days)	76.80	104.28	45.29	61.94	31.51	0.00
N. of Board Seats (by a VCF)	0.15	0.41	0.17	0.42	-0.02	0.09
N. of Venture Positions (by a VCF)	0.23	0.54	0.25	0.57	-0.03	0.06
Panel B: success measures						
Successful Exit	0.21	0.41	0.25	0.43	-0.04	0.00
IPO	0.04	0.19	0.04	0.19	-0.00	0.78
M&A	0.17	0.38	0.21	0.41	-0.04	0.00
N. of Venture Employees	292.22	1133.57	394.70	1518.06	-102.48	0.01
N^{notes}	3316		2389			

Notes: This table presents summary statistics for network portfolio ventures, defined as those having at least one peer venture that received a referral-based investment (see Section 2.5.2). Panel A details deal properties and outcome measures: *Deal Amount M$* reports the total funds raised in a round involving a focal deal, calculated from an N of 3031 (1820 non-network and 1211 network). Discrepancies in N are due to unreported amounts in Crunchbase. *Entry Round ID* is a factor variable assigning numerical values to each round type (e.g., Pre-Seed=1, Seed=2, Round A=3, etc.). *Time to Entry* measures the days from startup inception to the focal deal. *N. Part. Investors* indicates the size of the syndicate involved in the deal. *N. Board Seats/Positions* counts the seats or positions held by VCs. Panel B reports on venture success statistics: *N. of Venture Employees* tallies the venture's workforce. Exit outcomes (Successful Exit, IPO, M&A) are represented using dummy variables.

Table 2.7: The effect of deal referrals on peer venture's monitoring (N of board seats)

	Panel A: Hypothesis 3		Panel B: Hypothesis 3.1	
	(1)	(2)	(3)	(4)
Referral=1	0.0594**	0.0594**	0.0559*	0.0648*
	(0.0244)	(0.0244)	(0.0328)	(0.0335)
Referral=1 × Micro VC=1			-0.0137	-0.0305
			(0.0350)	(0.0354)
Referral=1 × Small VC=1			0.0372	0.0252
			(0.0315)	(0.0323)
Controls$_{(k+m+1)}$	Y	Y	Y	Y
FEs$_{(q)}$	Y	Y	Y	Y
k's deal year FEs		Y		Y
k's industry FEs		Y		Y
k's round FEs		Y		Y
Observations	5705	5705	5705	5705
R2	0.331	0.350	0.331	0.351

Notes: This table presents OLS coefficients assessing the impact of referrals on the monitoring of peer ventures within a portfolio. The analysis is limited to active VCFs within a five-year period surrounding each deal. Each portfolio includes the five investments closest in announcement date to the referred venture. The model incorporates baseline controls, fixed effects, a logarithmic transformation of syndicate size $Ln(1 + SyndicateSize_k)$, and fixed effects specific to the underlying deal. Columns (1) and (2) provide results for Hypothesis *H3*, and columns (3) and (4) for *H3.1*. Additionally, columns 2 and 4 include fixed effects for *Deal-Year*, *Sector*, and *Round* at the portfolio venture level. Standard errors (in parentheses) are clustered by V_k and by VCF. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: The impact on a peer portfolio's venture exit probability (Exit=1 (M&A or IPO)

	Panel A: Hypothesis 4		Panel B: Hypothesis 4.1	
	(1)	(2)	(3)	(4)
Referral=1	0.00458	-0.00670	0.00276	-0.00993
	(0.0230)	(0.0222)	(0.0273)	(0.0273)
Referral=1 $\times$ Micro VC=1			0.00600	0.00784
			(0.0325)	(0.0332)
Referral=1 $\times$ Small VC=1			-0.00105	0.00158
			(0.0386)	(0.0397)
Controls$_{(k+m+1)}$	Y	Y	Y	Y
FEs$_{(q)}$	Y	Y	Y	Y
k's deal year FEs		Y		Y
k's industry FEs		Y		Y
k's round FEs		Y		Y
Observations	5705	5705	5705	5705
R2	0.302	0.327	0.302	0.327

Notes: This table presents OLS coefficients assessing the impact of referrals on the exit outcomes of peer ventures within a portfolio. The analysis is limited to active VCFs within a five-year period surrounding each deal. Each portfolio includes the five investments closest in announcement date to the referred venture. The model incorporates baseline controls, fixed effects, a logarithmic transformation of syndicate size $Ln(1 + SyndicateSize_k)$, and fixed effects specific to the underlying deal. Columns (1) and (2) provide results for Hypothesis *H4*, and columns (3) and (4) for *H4.1*. Additionally, columns 2 and 4 include fixed effects for *Deal-Year*, *Sector*, and *Round* at the portfolio venture level. Standard errors (in parentheses) are clustered by V_k and by VCF. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9 Appendix

Table A2.1: Venture-level outcome statistics

	Non-Referred		Referred		Diff.	
Variable	Mean	SD	Mean	SD	df	p
Panel A: Focal venture outcomes						
Successful Exit	0.13	0.34	0.24	0.43	-0.11	0.00
IPO	0.03	0.16	0.03	0.18	-0.00	0.80
M&A	0.11	0.31	0.22	0.42	-0.11	0.00
Panel B: Previous venture outcomes (max.)						
Successful Exit	0.47	0.50	0.63	0.48	-0.15	0.00
IPO	0.01	0.10	0.01	0.12	-0.00	0.66
M&A	0.47	0.50	0.62	0.49	-0.15	0.00
N	217		220			

Notes: This table presents outcome statistics at the venture-founder level for referred ventures, which are supported by at least one deal involving an indirect social connection to a focal investor. Panel A details the exit statistics of focal ventures and founders, utilizing dummy variables. An *Exit* is recorded as one if either *IPO* or *M&A* is one. Panel B outlines statistics from a focal founder's prior startup. For founding teams with multiple serial founders, statistics are derived from the maximum values among them.

Table A2.2: The effect of deal referral on a VCF's exposure (H1 - alternative sample)

	Panel A: Ln(Time-to-Announcement)			Panel B: Ln(Deal Amount)		
	(1)	(2)	(3)	(1)	(2)	(3)
Referral=1	-0.150***	-0.149***	-0.102**	0.0997	0.0978	0.153**
	(0.0503)	(0.0514)	(0.0419)	(0.0665)	(0.0671)	(0.0678)
Eigenvector Centrality$_j$		-0.0201	0.0294		0.0240	-0.153
		(0.104)	(0.116)		(0.109)	(0.169)
Controls$_{(k+m-1)}$	Y	Y	Y	Y	Y	Y
FEs$_{(q-1)}$	Y	Y	Y	Y	Y	Y
Investor FEs			Y			Y
Observations	1109	1109	1109	1109	1109	1109
R2	0.479	0.479	0.792	0.764	0.764	0.879

Notes: This table presents OLS coefficients assessing the impact of referrals on a VCF's financial exposure. The analysis includes ventures with complete funding data. We measure financial exposure in Panel A using the logarithm of the number of days passed from venture inception to deal announcement. In Panel B, financial exposure is proxied using the logarithm of the deal amount in millions of USD. The analysis is conducted at the investor-venture-founder level, with baseline controls and venture fixed effects included in all specifications. Column (3) additionally includes Investor FE. *Referral* is an indicator of an indirect connection between a $Investor_i$ and a founder through a network peer ($Backer_b$). Controls include indicators for a founder board membership (current and previous), previous venture success, previous venture cessation, referee's lead investor status, a founder's experience in a focal technology sector, deal syndicate size, an investor's portfolio size, an investor's median first engagement time with portfolio ventures, an investor's median amount invested in opening rounds, and an investor's eigenvector centrality. Fixed effects are included for a venture inception year, tech-sector, financing round, and founder to control for unobserved heterogeneity at these levels. Standard errors (in parentheses) are clustered by V_i and by $Founder$. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.3: The effect of deal referrals on monitoring (alternative sample)

	Panel A: Hypothesis 2			Panel B: Hypothesis 2.1		
	(1)	(2)	(3)	(1)	(2)	(3)
Referral=1	-0.0317	-0.0227	0.00411	0.0107	0.0167	0.0316
	(0.0310)	(0.0322)	(0.0363)	(0.0540)	(0.0546)	(0.0584)
Eigenvector Centrality$_j$		-0.108*	-0.0524		-0.113*	-0.0593
		(0.0640)	(0.0932)		(0.0645)	(0.0935)
Micro VC=1				-0.186***	-0.191***	-0.0965
				(0.0432)	(0.0435)	(0.130)
Referral=1 $\times$ Micro VC=1				-0.00407	0.00121	0.0356
				(0.0550)	(0.0550)	(0.0645)
Small VC=1				-0.0702	-0.0723	-0.0793
				(0.0484)	(0.0487)	(0.0968)
Referral=1 $\times$ Small VC=1				-0.145**	-0.138**	-0.153**
				(0.0608)	(0.0610)	(0.0718)
Controls$_{(k+m)}$	Y	Y	Y	Y	Y	Y
FEs$_{(q-1)}$	Y	Y	Y	Y	Y	Y
Investor FEs			Y			Y
Observations	1109	1109	1109	1109	1109	1109
R2	0.158	0.160	0.566	0.190	0.192	0.573

This table presents OLS coefficients analyzing the effects of referrals on monitoring, as indicated by the number of board seats assigned to the VCF. The analysis only includes ventures for which we obtain complete funding data. Panel A examines the average effect, while Panel B explores the heterogeneous effects, categorized by VCF size as defined in Eq. 2.2. The analysis is conducted at the investor-venture-founder level, with baseline controls and venture fixed effects included in all specifications. Column (3) additionally includes Investor FE. *Referral* is an indicator of an indirect connection between a $Investor_i$ and a founder through a network peer ($Backer_b$). Standard errors (in parentheses) are clustered by V_i and by $Founder$. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.4: The effect of deal referrals on peer venture's monitoring (alternative sample)

	Panel A: Hypothesis 3		Panel B: Hypothesis 3.1	
	(1)	(2)	(3)	(4)
Referral=1	0.0779***	0.0765***	0.0792**	0.0771**
	(0.0270)	(0.0265)	(0.0341)	(0.0350)
Referral=1 × Micro VC=1			-0.000639	0.00289
			(0.0421)	(0.0424)
Referral=1 × Small VC=1			0.000748	-0.000533
			(0.0338)	(0.0357)
Controls$_{(k+m+1)}$	Y	Y	Y	Y
FEs$_{(q)}$	Y	Y	Y	Y
k's deal year FEs		Y		Y
k's industry FEs		Y		Y
k's round FEs		Y		Y
Observations	4624	4624	4624	4624
R2	0.331	0.354	0.331	0.354

Notes: This table presents OLS coefficients that assess the impact of referrals on the monitoring of peer ventures within a portfolio. The analysis includes only those ventures with complete funding histories. Monitoring is quantified by the number of board seats a VCF occupies on each venture's board of directors. The scope of the analysis is confined to active VCFs within a five-year window surrounding each deal, and each portfolio comprises the five investments closest in announcement date to the referred venture. The model integrates baseline controls, fixed effects, a logarithmic transformation of syndicate size $Ln(1 + SyndicateSize_k)$, and fixed effects specific to the underlying deal. Results for Hypothesis *H3* are reported in columns (1) and (2), and for *H3.1* in columns (3) and (4). Columns 2 and 4 also incorporate fixed effects for *Deal-Year*, *Sector*, and *Round* at the portfolio venture level. Standard errors, listed in parentheses, are clustered by venture V_k and VCF. Significance levels are indicated as: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A2.5: Placebo - N. Board Seats in a Peer Portfolio's Venture

	Panel A: Main sample			
	Panel A.1: Hypothesis 3		Panel A.2: Hypothesis 3.1	
	(1)	(2)	(3)	(4)
Referral=1	0.0268	0.0347	0.0393	0.0505
	(0.0260)	(0.0267)	(0.0381)	(0.0399)
Referral=1 $\times$ Micro VC=1			-0.0179	-0.0258
			(0.0335)	(0.0355)
Referral=1 $\times$ Small VC=1			-0.0266	-0.0283
			(0.0371)	(0.0380)
Controls$_{(k+m+1)}$	Y	Y	Y	Y
FEs$_{(q)}$	Y	Y	Y	Y
k's deal year FEs		Y		Y
k's industry FEs		Y		Y
k's round FEs		Y		Y
Observations	5703	5703	5703	5703
R2	0.321	0.348	0.322	0.349
	Panel B: Alternative sample			
	Panel B.1: Hypothesis 3		Panel B.2: Hypothesis 3.1	
	(1)	(2)	(3)	(4)
Referral=1	0.0379	0.0426	0.0570	0.0646
	(0.0314)	(0.0319)	(0.0441)	(0.0452)
Referral=1 $\times$ Micro VC=1			-0.0346	-0.0427
			(0.0406)	(0.0430)
Referral=1 $\times$ Small VC=1			-0.0215	-0.0221
			(0.0406)	(0.0427)
Controls$_{(k+m+1)}$	Y	Y	Y	Y
FEs$_{(q)}$	Y	Y	Y	Y
k's deal year FEs		Y		Y
k's industry FEs		Y		Y
k's round FEs		Y		Y
Observations	4623	4623	4623	4623
R2	0.320	0.349	0.321	0.350

Notes: This table presents OLS coefficients from a placebo test evaluating the effect of referrals on the monitoring of peer ventures within a portfolio. **Panel A** analyzes the entire sample of portfolio ventures, while **Panel B** focuses on those ventures for which complete funding data of their peers is available. Monitoring is measured by the number of board seats a VCF holds on each venture's board of directors. The analysis is limited to active VCFs over a five-year period around each deal, with each portfolio consisting of five randomly selected investments. The model incorporates baseline controls, fixed effects, a logarithmic transformation of syndicate size ($Ln(1 + SyndicateSize_k)$), and deal-specific fixed effects. Results for Hypothesis *H3* appear in columns (1) and (2), and for *H3.1* in columns (3) and (4). Additionally, columns 2 and 4 include fixed effects for *Deal-Year*, *Sector*, and *Round* at the portfolio venture level. Standard errors, displayed in parentheses, are clustered by venture (V_k) and VCF. Significance is noted as: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Chapter 3

Herding in the Market for Venture Acquisitions

Herding in the Market for Venture Acquisitions

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Abstract

We document herding effects in the market for startup acquisitions. We apply novel machine-learning techniques to generate dyads of technologically-related companies using 5,725 Israeli startups. Difference-in-differences models show that the acquisition of a startup by a foreign firm substantially increases the chances that a peer is acquired by another foreign firm. Consistent with informational herding, Israeli acquirers minimally react to foreign acquisitions of Israeli startups. Foreign acquirer response intensifies with the prominence of an initial acquisition, and is strongest for acquirers having weaker ties with Israel. Acquirers earn higher abnormal returns when they imitate their predecessors, suggesting positive learning effects from herding.

3.1 Introduction

In 2013, Google acquired social mapping company Waze for $1.3 billion dollars, making it the most lucrative exit for an Israeli venture at the time (Teig (2013)). After this initial acquisition, the panorama for Israeli ventures in the mobility space changed substantively (Frenkel (2020)), Apple bought car-sensor company PrimeSense for $300 million and Intel acquired Mobileye for $15 billion. According to anecdotal accounts, the acquisition of Waze put Israeli mobility ventures in the spotlight and, shortly after this acquisition, other foreign acquirers followed suit. This paper asks whether such initial acquisitions induce imitation by other potential acquirers, thereby improving acquisition prospects for technologically similar ventures located in a given entrepreneurial ecosystem. We address this question using international acquisitions as an empirical context.

The theoretical literature has identified several sources of herding (imitation). For instance, an entity may imitate the action of its predecessor because relying on the informative content of this action has a higher expected payoff than following one's own private signal (Banerjee (1992); Bikhchandani, Hirshleifer, and Welch (1992); Welch (1992)). Additionally, agents may imitate the action of others because correlated prediction errors lead to a "sharing the blame" effect (Scharfstein and Stein (1990)). Herding can also be triggered by the fact that some actions are more worthwhile when others perform them as well (Becker (1991)).

We examine herding effects in the market for venture acquisitions. Although these transactions represent the prevalent exit mode for ventures (Catalini, Guzman, and Stern (2019); Hellmann (2006)), they are fraught with uncertainties (Benson and Ziedonis (2010); Hellmann (2002); Higgins and Rodriguez (2006)), which often prevent acquiring firms from deriving positive returns (Andrade, Mitchell, and Stafford (2001)). These uncertainties, which have led acquisitions to be geographically concentrated (Almazan, De Motta, Titman, and Uysal (2010)), may induce firms to forgo attractive opportunities that emerge in less familiar markets. Firms could engage in herding when they have little private information about these markets and because the initial acquisition of a venture may generate positive payoff externalities. While herding in this context is a compelling hypothesis, it is also possible that firms refrain from imitation to the extent that there is a scarcity of suitable venture targets (Kamepalli, Rajan, and Zingales (2020)). Indeed, firms may not follow the example of an initial acquirer due to a depletion of opportunities, a surge in the targets' price, or to avoid exacerbating competition.

To study these issues, we employ data on 5,725 Israeli ventures that obtained financing between 2002 and 2019. Our rich data allow a full-fledged analysis of herding effects. We not only observe whether ventures are acquired, but also their sales price, the financing amount they raised, investor features, and the technologies they developed. Israel is an ideal empirical setting for our analysis. The country produces technologies that are relevant for domestic and foreign incumbents alike. As such, demand for Israeli ventures is fueled by both domestic and foreign firms. To the extent that opportunities in a given ecosystem are more uncertain for foreign than for domestic firms for geographical and/or cultural reasons, herding should be more relevant for the former than for the latter category of firms.[1] Accordingly, our analysis will evaluate whether there is herding in the market for venture

[1]Israel represents a unique entrepreneurial ecosystem with distinct characteristics relative to those in the US, Europe, and Far East Asia

acquisitions and, if so, whether such herding is motivated by information frictions.

Using descriptions of the ventures and their technologies, we implement a machine learning algorithm to generate dyads of companies developing similar technologies. This is a fundamental step in our analysis given that herding among acquirers should be more relevant if the technologies their target ventures develop are similar. Building on this analysis, we implement a difference-in-differences approach, comparing over time the exit outcomes of ventures whose peers were acquired by a foreign firm to the outcomes of control ventures whose peers did not experience such an exit. These controls are randomly chosen outside of the treated ventures' sectors of operation. We saturate the model with a wide array of fixed effects, including fixed effects for each dyad, subsector-by-year, and group of treated and control ventures.

We find that those ventures whose technologically similar peers were acquired by a foreign firm experience a subsequent 0.36 percentage point increase in the probability of being acquired by a foreign firm in a given year, relative to the control group. This is equivalent to a 61% increase in the mean. We examining the response of Israeli incumbents to the initial acquisition of a venture by a foreign company, we find instead that the treatment effect on the probability that a venture is acquired by an Israeli incumbent is only 0.1 percentage points, or a 29% increase relative to the outcome mean.

Once concern with these estimates is that despite the fine-grained set of fixed effects we include, which allow us to control for obvious confounding factors, the acquisition outcome of a peer may be determined by strategies previously implemented by the observed venture (Manski (1993)). To assess whether this may be the case, we perform an event study showing that the expected probability that a venture is acquired in the years preceding its peer's acquisition is not significantly different from that of the control group. The absence of pre-trends is also detected when we analyze a venture's intermediary outcomes, including its patent production and the amount of funds raised. The totality of these results suggests that the outcomes of an observed venture do not drive its peer's acquisition.

We perform additional analyses showing that our results are not driven by serial acquirers acquiring multiple Israeli ventures. Moreover, they show that the differential effects detected on foreign and domestic acquirers are neither entirely driven by differences in firm size nor by the fact that acquirers diverge in their sectoral specialization. Overall, these results suggests that acquirers engage in herding behavior to learn about opportunities in less familiar venture ecosystems.

We provide several additional findings that support the proposed herding mechanism. First, we show that the information value of an initial acquisition is strongest when two acquisition targets develop close technologies. Indeed, when we adopt more stringent criteria for selecting peers developing similar technologies, we find that ventures whose peers are acquired by a foreign company experience an 85% increase in their likelihood of going

(Bresnahan, Gambardella, and Saxenian (2001)). While some firms from these geographical areas have established R&D centers in Israel, somewhat reducing geographical distance, the cultural gap between Israeli ventures and foreign incumbents remains wide (Senor and Singer (2011)). A report by the Israel Venture Capital Research Center reveals that several US companies tend to regard Israel as a secondary market, acquiring its companies after having scouted opportunities in the US (IVC Research Center (2019)). For instance, Tom Leighton, CEO of Akamai, is quoted as saying "From the Technology point of view Israel is the most interesting place in the world *after* Silicon Valley."

through a similar exit, relative to the outcome mean. This is a considerably larger effect than the baseline effect described earlier. Conversely, herding effects among Israeli acquirers remain substantially smaller. Second, we show that while foreign acquirers react to the acquisition of Israeli ventures by other foreign firms, they are not responsive to acquisitions by Israeli firms. This result indicates acquirers only imitate peers with whom they share similar backgrounds and preferences. Third, we show that herding effects strengthen when the initial acquisition is undertaken by a prominent foreign acquirer and when such an acquisition has received widespread attention in the news. Fourth, we provide evidence that the less informed foreign acquirers –namely, non-US acquirers and foreign acquirers without an R&D center in Israel– respond more strongly to prominent acquisitions than to non-prominent acquisitions of Israeli ventures, relative to the better informed foreign acquirers. Finally, being associated with an initial prominent acquisition is more impactful than being associated with subsequent acquisitions. This suggests that prominent acquisitions of Israeli ventures trigger immediate herding effects, which dissipate over time once additional sources of information become available or the availability of suitable targets declines.

There are three alternative channels to herding in the venture acquisition market. One is that an initial acquisition spurs venture capitalists' (VCs) activities that enhance their portfolio ventures' value, making these companies more attractive to foreign acquirers. However, we show that investors do not invest larger amounts in their ventures after the technologically similar peers have been acquired. Relatedly, we could be capturing supply *and not* demand effects to the extent that an initial acquisition leads to more ventures seeking acquisition opportunities. However, we show that ventures whose peers were acquired by a foreign company sell at a higher price than their controls. Had our results been explained *solely* by supply effects, we would have observed a decline and not an increase in the sales price of treated ventures. Third, the acquisition of a venture by a foreign firm could be followed by further acquisitions because acquirers are exposed to the same technological or stock market shocks (Rhodes-Kropf and Robinson (2008); Rhodes-Kropf and Viswanathan (2004)). Here, we show that our primary effects do not change after replacing subsector-by-year fixed effects with the more fine-grained technology-keyword-by-year fixed effects. Moreover, we show that acquisitions of Israeli ventures are uncorrelated with acquisitions of US ventures. Specifically, we find that after an Israeli venture is acquired, US ventures developing similar technologies do not improve their acquisition chances relative to US ventures that produce dissimilar technologies.

To bring our exploration fully circle, we assess whether acquirers earn abnormal returns by acquiring ventures under herding. For one, acquirers may earn abnormal returns if herding allows them to seize opportunities arising from the Israeli venture ecosystem. For another, abnormal returns may be negative if acquirers follow the crowd even when the predecessors' actions have no informative content (Bikhchandani et al., 1992). We show that acquirers earn relatively higher abnormal returns when they imitate their predecessors, suggesting that by following the behavior of their predecessors, acquirers benefit from opportunities offered by the Israeli ecosystem.

Our paper makes an important contribution towards understanding the determinants of venture acquisitions. While firm quality (Catalini et al. (2019)), founder turnover (Conti and Graham (2020); Ewens and Marx (2017)), technological complementarities (Ma (2020)), proximity to potential acquirers (Conti and Guzman (2021)), VC characteristics (Ewens and Rhodes-Kropf (2015); Hochberg, Ljungqvist, and Lu (2007); Korteweg and Sorensen (2017)), and business cycles (Conti, Dass, Di Lorenzo, and Graham (2019); Nanda and Rhodes-Kropf (2013a)) have been shown to impact venture acquisitions, the focus of our study is on herding effects. To the best of our knowledge, this is the first paper providing evidence that firms imitate the acquisition behavior of their predecessors, particularly when uncertainty over opportunities in the venture acquisition market is high. With this last result, we also contribute to the literature examining information frictions inherent in investor-investee relationships involving ventures (Conti, Thursby, and Thursby (2013a); Conti, Thursby, and Rothaermel (2013b); Howell (2020); Hsu and Ziedonis (2013)). Our specific focus is on how firms cope with uncertainties about opportunities in the venture exit market. In this context, we advance the literature that has investigated the certification role played by VCs (Hsu (2004)), especially in initial public offerings (IPOs) (Megginson and Weiss (1991)), and the effect of patent applications in revealing private information on a venture's technology (Chondrakis, Serrano, and Ziedonis (2019)).

Finally, we contribute to the vast literature that has examined the determinants of merger waves, providing evidence of clustering of mergers in time and industry (Andrade et al. (2001); Harford (2005); Mitchell and Mulherin (1996)). While the literature has predominantly focused on misvaluation of financial markets and availability of liquidity as determinants of merger waves (Harford (2005); Rhodes-Kropf, Robinson, and Viswanathan (2005); Shleifer and Vishny (2003)), our focus is on the decision of acquirers to follow their predecessors to learn about opportunities emerging in less familiar venture ecosystems. By showing that acquirers derive abnormal returns when they follow their predecessors, we add to the debate as to whether acquisitions made during merger waves create value for acquiring shareholders or not (Duchin and Schmidt (2013); Maksimovic, Phillips, and Yang (2013)). While the literature has provided inconsistent results, our findings provide boundary conditions under which following the acquisition behavior of others maybe value-enhancing.

3.2 Data

3.2.1 Data sources

The data used in this paper is assembled from a variety of sources. The main dataset is constructed from the Israeli venture database available from the Israel Venture Capital (IVC) Research Center. Similar to the US Venture Capital Association, IVC collects detailed information on Israeli ventures' financing rounds and participating investors, founding location and date, technology, sector and subsector of operation, and exit outcomes (acquisitions and IPOs). Previous research has extensively used this database and validated it as an accurate representation of the Israeli high-tech venture ecosystem (Avnimelech and Teubal (2006); Conti and Guzman (2021)). From the IVC dataset we retained the population of 5,725 Israeli ventures that raised a financing round between 2002 and 2019 and were founded between 1998 and 2018. We consulted secondary sources to determine the location of the investors and their typology whenever it was missing. This supplementary information came primarily from investors' descriptions reported on their own webpages and the Bloomberg website, as well as from individuals' LinkedIn profiles.

We enriched this dataset further with information on the venture acquirers, available from Start-Up Nation Central. We used this latter source to distinguish acquirers according to whether they are Israeli or foreign and, in the case of foreign acquirers, according to whether or not their headquarters are in the US. Finally, we collected information on the patents that ventures applied for with the US Patent and Trademark Office (USPTO).[2]

Table 3.1 reports descriptive statistics that shed light on the characteristics of our sample ventures. As shown, Israeli ventures operate in the following sectors: cleantech, communications, IT & enterprise software, Internet, life sciences, semiconductors, as well as miscellaneous technologies.[3] Not surprisingly, the majority of the ventures (61%) are active in the communications, IT & enterprise software, and internet sectors, reflecting Israel's comparative advantage in these sectors.

The average venture in our sample raised a total of $8.06 million during the period we observe, although the distribution is skewed as illustrated by the low median value ($0.66 million). The venture financing was raised over an average of 1.72 rounds. IVC classifies venture investors into VCs, private equity firms, banks, advisory & management companies, technology firms, government, and private investors. Thirty-eight percent of the ventures raised VC funds and 16% received financing from US VCs. The average amount of funds a venture received from US investors is $5.15 million, and the average amount of US VC is $3.55 million.[4]

The average number of patents a venture applied for with the USPTO is 1.23, with a minimum of zero and a maximum of 191. Fourteen percent of ventures experienced an exit through either an IPO or an acquisition (or, in rare cases, a merger). The percentage of ventures that went public via an IPO is considerably smaller (2%) than the percentage of those that were acquired (12%). This is consistent with the distribution of venture outcomes found by Catalini et al. (2019). Moreover, given that the focus of this paper is on the market for venture acquisitions, we classified approximately 10 public companies that were subsequently acquired as ”acquired” ventures. Finally, 8% of the ventures were acquired by a foreign company, and in particular 6% were acquired by a US company.

⟨ Insert Figure 3.1 about here ⟩

3.2.2 Dataset construction

Building on Hoberg and Phillips (2010), and Guzman and Li (2022), we examine dyads of ventures operating in closely related technology areas. The goal is to assess how the acquisition prospects of a venture vary after its peer is acquired by a foreign company, relative to a control group of ventures whose peers were not acquired. A venture can be matched with more than a peer, based on technological similarity. Adopting this approach allows

[2] Israeli ventures typically apply for patents with the USPTO given that the US represents their main market

[3] Miscellaneous technologies typically display strong links with those developed in the communications and IT & enterprise software sectors

[4] Because we only have information regarding the amount ventures raised in each round and the participating investors, and not information regarding the amount invested by each investor, we make the assumption that when a US investor invests in a given round that investor represents the largest contributor to that round.

us to include a richer set of fixed-effects then if we only studied industry dynamics, and thus we can control for venture, dyad, and industry-year fixed effects.

To construct the dyads, we considered the keywords that IVC uses to describe a venture's technology. These keywords are very granular. For example, the technology that the company Waze develops is described by the following keywords: Mobile GPS, Social Mobile Application, Location Based Services, Social Commuting, and Geogaming. The keywords are available for approximately 74% of the sample ventures. In order to keep the 26% of the ventures that were not originally assigned any keywords in our sample, we implemented a machine learning algorithm to assign each ventures a set of technology keywords. This algorithm exploits the richness of the IVC data, which includes generic venture descriptions, as well as in-depth descriptions of the ventures' technologies and their targeted markets. Importantly, these descriptions, along with the keywords, are produced at around a venture's founding date and tend to remain unchanged over time. Thus, we can make the assumption that they reflect the technologies and products that the companies had started developing at the time they were founded. The details of the algorithm are provided in Section A.1 of the Appendix. As an output, the algorithm assigns each company a set of keywords. ventures with initially assigned keywords have the keywords updated by the algorithm to avoid potential bias deriving from systematic differences between ventures that have, and do not have, keywords. However, in a range of unreported tests we confirm that all our results are robust to keeping the original keywords and limiting our analysis to the 74% subsample with IVC assigned keywords.

Figure 3.1 reports validations of our keyword assignment method by comparing the overlap in keywords between two ventures in a dyad to other measures of relatedness.[5] These measures are: whether ventures operate in the same sector according to IVC and whether they share investors. In the top panel, from left to right, we show that the mean value of the overlap measure is largest for paired ventures that belong to the same subsector[6] and progressively declines for paired ventures operating in the same sector and for those assigned to the same broad area. In the bottom panel, we show a steady increase in the mean value of the overlap measure as the number of investors the ventures in a dyad have in common rises.

Next, using the assigned keywords, we define dyads of ventures developing similar technologies. These are all dyads of ventures founded within five years of one another, sharing at least three technology keywords, and operating in the same broad technology areas (that is, cleantech, life sciences, internet, and ITC).[7] In each dyad, we designate at random a "peer", which may be acquired first, and an "observed" venture, which may be treated by the acquisition event of its peer and may be acquired in the future.[8] We remove from the sample all dyads where the observed venture is acquired before the peer, since the former is not at risk of treatment.

For each treated venture, we build a control group by randomly selecting (with replacement) ten ventures

[5] Overlap in keywords is measured as $\frac{Num\_Shared\_Keyworks_{ij}}{min(Num\_Shared\_Keywords_i, Num\_Shared\_Keywords_j)}$.

[6] For example, the communications sector encompasses the following subsectors: broadband access, broadcast, enterprise networking, home networking, mobile applications, mobile infrastructure, NGN & convergence, optical networking, security, telecom applications, VoIP & IP telephony, wireless applications, and wireless infrastructure. We report the entire list of subsectors in Table A3.1 of the Appendix.

[7] ITC sectors are communications, IT & enterprise software, semiconductors, and miscellaneous technologies. The reason for incorporating the latter sectors into a unique broad area is that, having inspected the keywords IVC assigns to the ventures in order to describe their technology, we realized that the ventures operating in these sectors would often share at least one keyword.

[8] As a robustness check, we repeated this randomization several times and found that the coefficients of interest do not change on average.

whose peers were not acquired by a foreign company. These controls belong to the set of ventures that operate in a different sector but are founded in the same year as the treated venture. By adopting this approach, we control for shocks that affect the Israeli venture ecosystem at a given point in time and ensure that the acquisition of a venture's peer does not affect the controls' exit outcomes.

Overall, our approach yields 5,402 "observed" ventures matched to 5,495 peers, for a total of 133,198 dyads. The median number of peers per observed venture is 13, while the median number of acquired peers is one. Finally, we set up a panel in which we observe each venture in a given treated-control group during the period starting five years before a given acquisition event and ending ten years after. Relaxing this temporal cutoff does not change our results.[9] The data are truncated in 2020. As a result, the total number of observations employed in our panel is 1,191,267.

3.3 Empirical strategy

3.3.1 Empirical identification

The goal of our approach is to examine how the acquisition of an Israeli venture by a foreign firm affects the likelihood that the associated venture will be acquired. We take advantage of our method for constructing dyads to control for a large variety of fixed-effects in a difference-in-differences specification that compares the effect of a peer acquisition on an observed venture relative to controls whose designated peer was not acquired. Specifically, for every venture i associated with an acquired peer j and control ventures in group g, we estimate:

$$\begin{aligned} Y_{i,j,t} = \alpha PostAcquisition_{g,t} + \beta PostAcquisition_{g,t} x Peer\, Acquired\, by\, Foreign\, Firm_i + \\ + \omega_{i,j} + \psi_g + \mu_{s(i),t} + \delta_i + \sigma_j + \gamma_{s(j),t} + \epsilon_{i,j,t}. \end{aligned} \tag{3.1}$$

where Y_{ijt} is the probability that venture i, paired with venture j, is acquired in year t. We examine variants of this outcome, specifically focusing on acquisitions by foreign companies, which we contrast to acquisitions by domestic companies. Peer Acquired by $ForeignFirm_i$ is our treatment indicator, which takes a value of one if peer j of venture i is acquired by a foreign firm and zero otherwise. $PostAcquisition_{gt}$ is a time varying binary indicator that becomes one for all the ventures in a treated-control group g after the peer j of a treated venture is acquired by a foreign firm. This indicator captures a time trend common to both the treated ventures and their controls. The coefficient of interest is β, which is associated with the interaction between Peer Acquired by $ForeignFirm_i$ and $PostAcquisition_{gt}$. This coefficient measures the average change in the likelihood that a venture is acquired in year t after its peer is acquired by a foreign company relative to the control group. A β greater than zero would be consistent with herd behavior among acquirers, to the extent that—all else equal—the

[9] Table A3.10 shows that the results remain qualitatively invariant when we examine the period starting five years before a given acquisition event and ending two years after.

initial acquisition by a foreign company induces other firms to expand their demand for Israeli ventures developing similar technologies to the initial acquiree. In our specification, the effect of $PostAcquisition_{gt}$ is absorbed by our fixed effects.

The empirical concern here is that the exposure to a given acquisition event is unlikely to be random. Such an exposure may be correlated with unobserved factors, including characteristics of an observed venture and its peer, as well as technology trends, that could confound estimates of Eq. 3.1. To address this concern, we follow the literature on peer effects and saturate our main specification with fixed effects that absorb venture and dyad fixed differences, and control for group unobservables over time (see, for e.g., Blume, Brock, Durlauf, and Ioannides (2011); Rockoff (2004)). Specifically, δ_i and σ_j are fixed effects for the observed venture and its peer. ω_i, j denotes the fixed effect for the i, j dyad, while ψ_g represents the fixed effect for group g encompassing a treated venture and its controls. Moreover, $\mu_{s(i),t}$ is a venture's subsector-by-year fixed effect, while $\gamma_{s(j),t}$ is a j's subsector-by-year fixed effect. The list of fine-grained subsectors is available in Appendix Table A3.1. In robustness tests described later, we substitute subsector-by-year fixed effects with the more granular keyword-by-year fixed effects.

Despite these fixed effects, a concern is that the acquisition of a peer j is the reflection of unobserved time-varying strategies implemented by venture i (Manski (1993)). To address this issue, we will perform a battery of tests showing that there are no pre-trends in the estimated acquisition probability of an observed venture and also in the venture's estimated patent output and likelihood of receiving venture capital. We will also add these time-varying controls in our regressions showing that the effects of interest minimally change.

3.3.2 Descriptive statistics

Table 3.2 and Table 3.3 report summary statistics at the dyad and dyad-year levels, distinguishing between ventures that are treated and not with their peer acquisition by a foreign company. These descriptive statistics offer a first glance into the herding mechanism that we plan to investigate. For instance, Table 3.2 shows that the proportion of ventures that experience an exit (IPO or acquisition) is 14% if such ventures are matched with a peer that was acquired by a foreign firm (Treatment=1), while it is 9% if the ventures' peers are not acquired by a foreign firm (Treatment=0). This gap widens once we consider acquisitions only. Exploring this exit mode further, we note that the proportion of observed ventures that are acquired by a foreign company is 8.9% in the treated group and 4.9% in the non-treated group. This difference of 4 percentage points is statistically significant and it is mostly driven by US firms' acquisitions of Israeli ventures. The difference between the treated and non-treated group is instead reduced to 1.5 percentage points when we examine acquisitions by Israeli firms as an exit outcome. Conditioning on those observed ventures that were acquired and for which we have sales price information, the sales price is higher for ventures in the treated group than for those in the control group. Finally, we report significant differences between treated and non-treated ventures with respect to the amount of funds they raise pointing to the importance of controlling for characteristics of the ventures and the sector in which they operate.[10] The summary statistics at

[10]As reported in Table A3.2, the difference between treated and non-treated ventures with respect to the amount of funds they raise in the first five years of inception is no longer statistically significant after we control for trends in the subsector in which they operate.

the dyad-year level reported in Table 3.3 are consistent with the dyad-level statistics just discussed.

Figure 2 provides additional insights into the examined herding mechanism. Here, we show that the acquisitions of Israeli ventures are not isolated phenomena. Once an initial acquisition takes place, others follow. This is especially evident in relatively ”new” subsectors, such as mobile applications, security, and enterprise applications.

⟨ Insert Table 3.2, Table 3.3 and Figure 3.2 about here ⟩

3.4 Results

We next proceed to present our empirical results on herding in the market for venture acquisitions. Section 3.4.1 describes the main difference-in-differences results. Section 3.4.2 sheds light on the mechanisms driving our results. Section 3.4.3 discusses possible alternative channels to herding, and Section 3.4.4 presents miscellaneous robustness checks.

3.4.1 Main estimates

We estimate the effect of a peer being acquired by a foreign firm on an observed venture's exit outcomes. The results are reported in Table 3.4. Column 1 begins by assessing how the acquisition of a peer affects a venture's likelihood of exiting, via either an acquisition or IPO. The positive coefficient of $PostAcquisition_{gt}$ suggests the existence of a common trend. After the acquisition of a peer, the likelihood of experiencing a liquidity event in t increases by 1.9 percentage points, on average, for the control ventures. At least in part, this increase follows mechanically from the condition we have established that the focal ventures can only experience a liquidity event after their peer is acquired.

Our coefficient of interest is the one associated with the interaction between $PostAcquisition_{gt}$ and *PeerAcquiredbyForeignFirm*$_i$. The estimate is positive and significant and its magnitude indicates that ventures improve their likelihood of experiencing an exit by 0.43 percentage points after their technologically related peers are acquired by a foreign firm, relative to the control group. This corresponds to a 40% increase in the outcome mean.

In column 2, we examine specifically venture acquisition outcomes. As shown, the exit results reported in column 1 are driven by acquisition events. Treated ventures are 0.47 percentage points more likely to be acquired in a given year after the acquisition of a peer: a 49% increase in the outcome mean. These findings indicate that -all else equal- the initial acquisition of an Israeli venture induces further acquisitions, thereby improving the overall acquisition prospects for Israeli ventures.

We next examine the reaction of foreign acquirers and contrast it to that by domestic acquirers. For this purpose, we decompose the observed ventures' acquisition outcomes according to whether the acquirers are foreign (column 3) or domestic (column 4). Our intuition is that, because information problems are more severe for foreign than for domestic acquirers, due to geographical and/or cultural distance, herding effects should be stronger for foreign acquirers. Relative to the mean, the common time trend is the same for the two outcomes examined. Regardless of whether the examined outcome is an acquisition by a foreign firm (column 3) or an acquisition by an Israeli firm (column 4), untreated ventures increase their likelihood of achieving these exits by approximately 178% post-treatment. The same time trend for both acquisition outcomes suggests that acquisition events follow similar dynamics, regardless of the acquirer's nationality.

Moving to our coefficient of interest, which is the one associated with the interaction between $PostAcquisition_{gt}$ and $PeerAcquiredbyForeignFirm_i$, we show that it is positive and significant regardless of the acquisition outcome examined. However, the magnitude meaningfully differs across outcomes. In particular, column 3 reports an increase of 0.37 percentage points in the likelihood that a venture is acquired by a foreign firm relative to the control group, an increase that corresponds to a 61% increment in the outcome mean. In contrast, the coefficient reported in column 4 is much lower, 0.11 percentage points, corresponding to a 29% increase in the mean. It is important to note that these results are not driven by serial acquirers acquiring multiple Israeli ventures. In fact, the incidence of cases in which a venture and its peer are acquired by the same acquirer is less than 1% in dyads where both a venture and its peer are acquired.

⟨ Insert Table 3.4 about here ⟩

Figure 3.3 examines the described effects within an event study framework. To do so, we modify Eq. 3.1 by substituting the $PostAcquisition_{gt}$ indicator with binary variables for each of the pre- and post-treatment years. This dynamic difference-in-differences specification allows us to compare the outcomes of a venture whose peer was acquired by a foreign firm to the control group, in each year before and after the acquisition event. We control for the full set of fixed effects listed in Eq. 3.1. The top panel reports the effects on venture acquisitions by foreign firms, and the bottom panel displays the effects on acquisitions by Israeli firms. We note three important patterns. First, there are no significant pre-trends regardless of the outcome examined, which suggests that our approach is able to account for selection into treatment and that a peer's acquisition is not the reflection of time-varying strategies implemented by the observed venture. Second, the top figure displays a large and immediate increase in the probability that venture i is acquired by a foreign company starting from year 0. The effects remain large up until year +4 and decline afterwards, suggesting that alternative information sources may emerge over time or that the demand by foreign firms may progressively fade along with the availability of suitable targets. Finally, when examining the probability that a venture is acquired by an Israeli firm at the bottom of Figure 3.3, we observe that the treatment effects during and after the treatment year are considerably smaller than those reported at the top of Figure 3.3 and noisier.

⟨ Insert Figure 3.3 about here ⟩

To further support the evidence reported in Figure 3.3, we perform an event study analysis for two relevant ventures' intermediate performance outcomes: the number of US patents ventures apply for and the likelihood of obtaining VC investment. The rationale is that if an observed venture's time-varying strategies affect both its acquisition prospects and those of the associated peer, we should observe pre-trends in the intermediate outcomes analyzed. The top panel of Figure 3.4 reports the event study for an observed venture's yearly number of US patent applications, while the bottom panel examines a venture's likelihood of receiving VC funding in a given year. For the latter event study, we only consider those treated ventures that were not acquired since acquired ventures mechanically stop raising funds and this would bias our results.

The top panel shows that treated ventures do not apply for more US patents than their controls, both before and after their peer's acquisition. Similarly, the bottom panel shows that treated ventures are no more likely to attract VC funds than their controls, both before and after their peer's acquisition. The totality of these results suggests that our approach reasonably addresses the reflection problem. Moreover, the evidence presented in the bottom panel speaks against the possibility that our results are driven by VCs investing more in Israeli ventures in response to an acquisition, thereby making these ventures attractive to potential acquirers.

⟨ Insert Figure 3.4 about here ⟩

Overall, these results suggest that the initial acquisition of an Israeli venture by a foreign company induces other firms, especially foreign ones, to seize acquisition opportunities in Israel. These findings are consistent with the idea that opportunities in a given ecosystem are more uncertain for foreign than for domestic firms and, thus, the expected payoffs from herding are higher for the former than for the latter firms. In the next sections, we explore the mechanisms behind our results and examine additional alternative interpretations.

3.4.2 Mechanisms

Having shown that ventures improve their chances of being acquired, especially by foreign firms, after their peers have been acquired by foreign companies, this section delves into the channels through which herding among acquiring firms operates.

Technological similarity

We start by assessing the role of the technological similarity between two target ventures in shaping herding behavior among acquirers. It is plausible that the positive externalities generated by an initial acquisition are larger the more similar the technologies two ventures produce. To explore this conjecture, we adopt a more stringent criterion for defining dyads of technologically similar ventures. Specifically, we impose not only that a dyad ij shares at least three technology keywords, but also that at least one of those keywords is among the three most relevant for describing i's and j's technologies according to our machine learning algorithm.[11]

The results from estimating Eq. (3.1) are reported in Table 3.5. After their peers have been acquired by a foreign company, treated ventures increase their likelihood of achieving an exit (column 1) and of being acquired (column 2) by 0.55 and 0.65 percentage points, respectively, relative to the control group. These effects are larger than those reported in Table 3.4 given that they represent a 52% and a 71% increase in the outcome means, respectively.

[11] Refer to Appendix A.1 for further details.

Moreover, the effect intensifies in column 3, where the analyzed outcome is the likelihood that a venture is acquired by a foreign company in t. Here, the coefficient associated with the interaction between $PostAcquisition_{gt}$ and $PeerAcquiredbyForeignFirm_i$, implies that -after a peer is acquired by a foreign company treated ventures experience an additional 0.48 percentage point increase in their likelihood of being acquired by a foreign company relative to the control group, equivalent to an average 84% increase in the unconditional probability. Reassuringly, this effect remains similar (85%) in column 4, where we adopt a conservative approach and substitute subsector by year fixed effects with technology keywords by year fixed effects.[12] As we mention in Appendix A.1, there are more than 700 keywords describing the venture technologies, which allow us to more precisely control for technology shocks that could trigger acquirer reactions regardless of mimicry.

The results reported in column 5 for the likelihood that an Israeli ventures is acquired by a domestic company show that the coefficient associated with the interaction between $PostAcquisition_{gt}$ and $PeerAcquiredbyForeignFirm_i$ continues to be smaller both in absolute and relative terms compared to the coefficients reported in columns 3 and 4. Moreover, the magnitude of the coefficient declines by 23% in column 6, once we add technology keywords by year fixed effects. The reported coefficient in this column implies that ventures whose peer was acquired by a foreign company experience an average 41% increase in their likelihood of being acquired by a domestic company relative to the unconditional probability. Overall, these results are consistent with a herding mechanism whereby the value of an initial acquisition by a foreign firm increases with the technology similarity between two ventures in a dyad and continues to be largest among foreign acquirers.

⟨ Insert Table 3.5 about here ⟩

Acquirer background

Next, we focus on foreign acquirers and evaluate the type of predecessors they are more likely to imitate. It is plausible that foreign acquirers are more prone to follow the strategies of their foreign rather than their domestic predecessors to the extent that they trust or value the former predecessors relatively more. To verify this hypothesis, we modify Eq. (3.1) and substitute the Peer Acquired by $ForeignFirm_i$ indicator with a binary variable that takes the value of one if i's peer j is acquired by an Israeli firm and zero otherwise. We regenerate the treated-control groups gs adopting the same criteria as those listed in Section 3.2, except that this time the treatment of interest is the acquisition of a given peer j by an Israeli company. The results are reported in Table 3.6. Consistent with our conjecture, column 1 shows that, after a peer is acquired by an Israeli firm, the associated observed venture does not significantly improve its chances of being acquired by a foreign firm relative to the control group. The effect is not only statistically insignificant, but its magnitude is also very small.

⟨ Insert Table 3.6 about here ⟩

[12]The keywords we use are those ranked first for importance in terms of describing a venture's technology.

The prominence of an initial acquisition

In our third analysis, we assess whether herding among foreign acquirers varies depending on how prominent the initial acquisition of a peer j by a foreign firm is. We define prominent acquisitions as those enacted by prominent acquirers. These acquirers are companies, such as Apple, Cisco, Google, IBM, and Oracle, which figure among the top acquirers in the IVC and Crunchbase datasets.[13] These are companies at the technology frontier and, thus, imitating their strategies may be relatively more valuable. We implement the analysis by modifying Eq. (3.1) and decomposing the $PeerAcquiredbyForeignFirm_i$ variable into two indicators, respectively denoting prominent and less prominent acquisitions of Israeli ventures by foreign companies. Similarly, we generated two $PostAcquisition_{gt}$ binary indicators: the first takes value one after a peer j is acquired by a prominent foreign firm and zero otherwise; the second becomes one after a peer j is acquired by a less prominent foreign firm. The results are reported in Table 3.7.

Column 1 shows that the coefficient of the interaction between $PostAcquisition_{gt}$ and the indicator for whether a peer was acquired by a prominent foreign acquirer is 51% larger than that associated with the interaction between $PostAcquisition_{gt}$ and the indicator for whether a peer was acquired by a less prominent foreign acquirer. The non-prominent acquisition of a peer has a significant impact, albeit relatively smaller, on the likelihood that a treated venture is acquired by a foreign company compared to the control group.

In column 2, we refine the notion of prominent acquisitions and retain only those that received widespread media attention and whose sales price is above the sector median for a given year. To measure media attention, we collected from LexisNexis news reports concerning the acquisition of a venture that were published between six months before and six months after the acquisition event. Building on these data, a prominent acquisition is considered to have received widespread media attention if the number of news reports mentioning it is above the sector median. As reported, the gap between the difference-in-differences estimates associated with prominent and less-prominent foreign acquisitions increases to 143%. Overall, these results indicate that herding among foreign acquirers intensifies with the prominence of an initial acquisition.

⟨ Insert Table 3.7 about here ⟩

Delving deeper into our prominent acquisition results, we examine whether there is any difference between less informed and better informed foreign potential acquirers in the way they react to the prominence of an initial acquisition. Accordingly, we distinguish between the likelihood that a venture is acquired by a US acquirer and the likelihood that it is acquired by either a European or an Asian acquirer. We make this distinction because US firms have stronger ties with the Israeli venture ecosystem than other foreign firms and, thus, they should be relatively more informed about acquisition opportunities in this ecosystem. In a similar vein, we distinguish between the likelihood that a venture is acquired by a foreign acquirer with an R&D center in Israel and the likelihood that it is acquired by a foreign acquirer without such an R&D center, under the assumption that the former acquirer is better

[13] The complete list of prominent acquirers is provided in Appendix Table A3.3.3.

informed than the latter. The results are reported in Table 3.8. We adopt the same definition of prominence as that employed in column 2 of Table 3.7. As reported in column 1 of Table 3.8, a venture becomes 0.57 percentage points more likely to be acquired by a US firm as a result of an initial prominent acquisition, while the increase is only 0.27 percentage points when the initial acquisition is less prominent. This 108% gap in effects widens to 300% when we instead examine the likelihood that a venture is acquired by either a European or an Asian firm (column 2). Similarly, the results in column 3 show that a venture becomes 0.18 percentage points more likely to be acquired by a foreign firm with an R&D center in Israel following an initial prominent acquisition, while the increment is only 0.1 percentage points when the initial acquisition is less prominent. The 81% difference in effects increases to 169%, when the outcome examined is the likelihood that a venture is acquired by a foreign firm with no R&D center in Israel (column 4). Overall, these results provide a strong indication that the less informed foreign acquirers respond more strongly to prominent acquisitions than to non-prominent acquisitions of Israeli ventures by other foreign firms, relative to the better informed foreign acquirers.

⟨ Insert Table about here ⟩

Acquisition dynamics

To conclude this section, we examine whether an observed venture's acquisition outcome is more sensitive to earlier or later foreign acquisitions of its technologically similar peers, and whether any reaction depends on the prominence of a given acquisition. An initial pioneer acquisition should matter more than subsequent acquisitions for at least two reasons. First, new sources of information may become available over time that reduce the rationale for herding (Bikhchandani et al. (1992)). Second, the scarcity of suitable targets may be such that, as firms acquire Israeli ventures, the remaining targets could be less appealing to potential acquirers. Building on our earlier findings regarding prominent acquisitions, we expect the effects of pioneer acquisitions to be amplified if they are enacted by prominent acquirers. To implement this analysis, we condition on those instances in which the peer j of a given venture i is acquired by a foreign company and rank these acquisition events from the earliest to the most recent. We then examine how i's chances of being acquired by a foreign company vary pre- and post-treatment, comparing earlier to more recent treatments and, moreover, contrasting prominent with less prominent treatments.

The results are reported in Figure 3.5. In Panel A, we plot the time coefficients pre and post the prominent acquisition of i's peer j by a foreign company, having distinguished between the earliest and the second acquisition of j. In line with our conjecture, we find that the earliest acquisition produces stronger effects than the most recent one. Panel B zooms in on the earliest foreign acquisitions, contrasting prominent with non-prominent acquisitions. Remarkably, the treatment effects of a pioneer (i.e., earliest) acquisition are greater than zero only if such an acquisition is prominent. A similar pattern as in Panel A is displayed in Panel C, where we contrast the earliest prominent acquisition of a peer j by a foreign company with the third of such events. Finally, Panel D compares the second to the third prominent acquisition of i's peers. Here, we continue to find that the earlier prominent acquisition of i's peer j by a foreign acquirer generates stronger effects than the more recent treatment, although the difference in effects is less pronounced. Overall, these results strongly suggest that prominent acquisitions of Israeli ventures trigger immediate herding effects, which dissipate over time once the information value of an initial acquisition fades or the availability of suitable targets declines.

⟨ Insert Figure 3.5 about here ⟩

3.4.3 Alternative interpretations

Thus far, we suggested that herding behavior among acquirers is motivated by information frictions. However, there are several other alternative interpretations, which we discuss and address in this subsection.

Foreign firms are better capitalized than domestic firms

We begin by considering the possibility that our results are driven by the fact that foreign firms are better capitalized than domestic firms rather than by information frictions which differentially affect the two acquirer types. Indeed, the literature has provided evidence that better-capitalized firms are more likely to join merger waves (Maksimovic et al. (2013)).

We assess the relevance of this alternative explanation by distinguishing between whether the peer is acquired by a large foreign company or by a smaller one. The rationale is that if differences in capitalization were the key driver of our findings, then these findings would be completely driven by larger foreign acquirers. Large firms are those such as Dell, General Electrics, IBM, Intel, Oracle, and Cisco, that are in the top quartile for their size distribution. The results of this test are reported in Table A3.4. Although treated ventures are relatively more likely to be acquired by a large acquirer than by a smaller one, the effect of the treatment on the likelihood that a venture is subsequently acquired by a smaller foreign firm remains sizable. After a peer is acquired by a foreign firm, the associated observed venture becomes 0.22 percentage points more likely to be acquired by a smaller foreign firm relative to the control group; equivalent to a 54% increase in the mean.

Acquirers responding to technology shocks

A related possibility is that firms - especially foreign ones, which are better capitalized- join merger waves in response to technology shocks without imitating each other. To investigate this possibility, we assess how the acquisition of an Israeli venture by a US firm is related to the acquisition opportunities of other US ventures developing similar technologies as the acquired Israeli company. If acquirers react to the same technology shocks without mimicry, the acquisition of an Israeli venture should be positively related to the acquisition prospects of technologically related US ventures.

To implement this analysis, we estimate a difference-in-differences model similar to the one described in Section 3.3.1. Specifically, we examine whether the acquisition of an Israeli venture by a US firm improves the likelihood that a US venture developing a similar technology to the Israeli company is subsequently acquired. The control group is represented by US ventures developing different technologies from those of the Israeli acquirees.

To build the sample, we first identified all the Israeli ventures acquired by a US company in the Crunchbase database. We then assigned a random sample of US ventures to the acquired Israeli ventures, dividing the former into two groups: those sharing at least three technology keywords (assigned by Crunchbase) with the Israeli acquirees and those sharing fewer than three keywords. If the alternative explanation mentioned above drives our results, then the acquisition prospects of the first group of US ventures should be positively related to the acquisition of the Israeli companies -given technological closeness- relative to the second group, which represents the control. Similar to the conditions we imposed in our main analyses, we excluded those US ventures that had an exit prior to the acquisition date of the associated Israeli company. We further limited the US ventures to those located in California, Massachusetts, and New York.[14]

The results are reported in Table 3.9. The dependent variable is the probability that a US venture i, paired with an Israeli venture j, is acquired in year t. The $PostIsraeliAcquisition_{gt}$ variable is a (0/1) indicator that becomes 1 after an Israeli venture is acquired, for all the US ventures associated with the Israeli company. $TechnologicallySimilar_i$ is an indicator identifying all the US ventures sharing at least three technology keywords with the associated Israeli venture. The results in column 1 show that after an Israeli venture is acquired, US ventures developing similar technologies as the initial acquiree do not improve their chances of being acquired relative to US ventures that produce dissimilar technologies. This result is confirmed in column 2, where the variable $TechnologicallySimilar_i$, instead, identifies all the US ventures sharing at least four technology keywords with the acquired Israeli venture. Overall, these findings provide a strong indication that our effects are not driven by firms simultaneously responding to technology shocks.

⟨ Insert Table 3.9 about here ⟩

Foreign and domestic acquirers specializing in different sectors

Another possibility is that the differential reactions of foreign and domestic acquirers we observe are driven by the fact that foreign acquirers are relatively more active in sectors that offer better opportunities. These sectors could be ICT sectors where Israel has developed significant knowhow. Table A3.5 shows that the proportion of foreign and domestic acquisitions of Israeli ventures does not significantly vary across sectors, except for semiconductors. Therefore, as a robustness check, we re-run all the main models reported in Table 3.4, excluding semiconductor ventures. Reassuringly, the results displayed in Table A3.6 show that the relevant effects remain very similar to those previously discussed, both in terms of magnitude and significance.

Foreign acquirers in search of valuable assets

Another explanation for our findings could be that foreign firms acquire Israeli ventures to incorporate valuable assets, including human capital, that are disproportionately concentrated in Israel. To investigate whether this may

[14] As Conti and Guzman (2021) have shown, most of the Israeli ventures that migrate to the US establish their headquarters in these three states. Hence, any effect stemming from the acquisition of Israeli ventures should be stronger in these regions.

be the prevalent explanation of our findings, we estimate Eq. (1) in the subsample excluding ventures developing security technologies. These are technologies in which Israel an expertise and, therefore, where valuable assets are concentrated. Reassuringly, the results reported in Table A3.7 continue to show strong herding effects among foreign acquirers.

Foreign acquirers in search of valuable assets

Another explanation for our findings could be that foreign firms acquire Israeli ventures to incorporate valuable assets, including human capital, that are disproportionately concentrated in Israel. To investigate whether this may be the prevalent explanation of our findings, we estimate Eq. (1) in the subsample excluding ventures developing security technologies. These are technologies in which Israel an expertise and, therefore, where valuable assets are concentrated. Reassuringly, the results reported in Table A3.7 continue to show strong herding effects among foreign acquirers.

Supply effects in the market for venture acquisitions

An alternative interpretation of our findings is that they could be driven by supply rather than demand effects to the extent that an initial acquisition entices more ventures to seek acquisition opportunities. To address this concern, we examine a venture's sales price upon an acquisition. The rationale is that if we captured supply effects only, then we would observe a decline in the sales price of ventures whose technologically similar peers were acquired by a foreign company. We estimate a cross-sectional model limiting the sample to dyads where the observed venture was acquired:

$$Y_{ij} = \alpha PeerAcquiredbyForeignFirm_i + \beta Controls_i + \gamma Controls_j + \omega_g + \mu_i + \tau_i + \epsilon_{ij} \tag{3.2}$$

The outcome Y_{ij} is defined as the price at which venture i in dyad ij was sold (expressed in natural logarithm). Since this information is only available for 67% of the acquired ventures, we estimate an alternative specification where we set the missing values to zero and generate an indicator for ventures that are above the median of the sectoral distribution of sales prices. According to Nanda and Rhodes-Kropf (2013b), missing values should correspond to cases in which ventures were acquired at a negligible price.[15] $PeerAcquiredbyForeignFirm_i$ is an indicator variable that takes value one if i's peer j is acquired by a foreign firm and zero otherwise. Because we estimate a cross-sectional model, we do not include observed or peer venture fixed effects. However, we include a fixed effect for the group g encompassing a treated venture and its controls (ω_g), a fixed effect for i's establishment year times sector (μ_i), and a fixed effect for i's exit year times sector (τ_i). We also control for the total amount of funds i and j raised by the time they were acquired, as well as for the total number of US patents the ventures were

[15] This is a plausible assumption. For example, Table A3.8 reports that acquired ventures with missing sales price information raise smaller VC amounts than acquired ventures with sales price information.

granted. These variables control for relevant aspects of i's and j's quality.

The results are displayed in Table 3.10. Reported standard errors are clustered by treated-control groups and by i's founding year. The dependent variable in column 1 is the natural logarithm of an acquired venture's sales price. In column 2, we examine the indicator identifying ventures in the top quartile of the sales price distribution. As reported in column 1, while the effect of a peer being acquired by a foreign company on an observed venture's sales price is positive, it is not significantly different from zero at conventional levels. In column 2, instead, we find that treated ventures are 3.6 percentage points more likely to be acquired at a high price relative to the control group and that effect is significant at the 5% level. Overall, these results speak against the possibility that our main findings are solely driven by supply effects. Had we captured supply effects only, we would have observed a decline and not an increase in the sales price of treated ventures.

⟨ Insert Table 3.10 about here ⟩

3.4.4 Miscellaneous robustness tests

For completeness, we include in the Appendix four additional miscellaneous robustness tests. In Table A3.9, we show that the results remain qualitatively invariant when we restrict the analysis to the period starting five years before a given acquisition event and ending two years after. In Table A3.10, we add several time-varying characteristics pertaining to the venture, its peer, and the dyad to our main equation specification. The time-varying controls we include are: the cumulative amount of funds raised by each venture (and the corresponding interaction), the cumulative amount of US VC funds raised by each (including the interaction), and the cumulative number of US granted patents each applied for (including the interaction). In Table A3.11, we report the main analyses having drawn the control group from ventures operating in the same sector, but in a different subsector, as the treated ventures. Table A3.12 presents the results from restricting the set of foreign acquirers to US firms. The estimates are similar to the main effects already discussed.

3.4.5 Returns to acquisitions under herding

To bring our exploration full circle, we assess whether acquirers earn abnormal returns by acquiring ventures under herding. To do so, we focus on the set of acquired ventures and determine the acquirers' abnormal returns at acquisition announcements relative to other firms, depending on whether the acquired ventures are associated with previously acquired peers.

For this analysis, we collected daily NASDAQ stock prices from Refinitiv DataStream -formerly Thomson Reuters DataStream. We then computed for each stock its daily abnormal returns following the procedure indicated by Fama and French (1993). Specifically, we calculated the expected returns of each NASDAQ stock by estimating a CAPM model for a stock's daily returns as a function of the following three variables: 1) the stock's market portfolio excess returns over a risk-free asset, 2) its market capitalization, and 3) the book-to-market ratio. The predicted values obtained from these regressions represent the stocks' expected returns. Successively, we computed the abnormal returns, which are defined as the difference between the realized stock returns and the expected returns. In the last step, we estimate the following regression for the stocks' cumulative abnormal returns:

$$CAR_{ijt} = \alpha Herd_{ijt} + \beta FirstAcq_{\cdot ijt} + \gamma Post_{jt} + \delta Post_{jtijt} + \Lambda Post_{jt} FirstAcq_{\cdot ijt} + \epsilon_{ijt} \tag{3.3}$$

CAR_{ijt} is the cumulative abnormal return on stock i for day t around acquisition j. $Herd_{ijt}$ is an indicator for whether stock i belongs to the acquirer involved in acquisition j, and this acquisition follows prior acquisitions in the same technology space. $FirstAcq_{\cdot ijt}$ is an indicator for whether stock i is of the acquirer involved in acquisition j, and this acquisition is the first acquisition in a given technology space. $Post_{jt}$ identifies the post-acquisition period for acquisition j.

The results are reported in Table 3.11. In column 1, we show that acquirers earn higher abnormal returns when they imitate their predecessors than when they do not, although the coefficient of the interaction between $Post_{jt}$ and $Herd_{ijt}$ is noisily estimated. In column 2, where the examined outcome is an indicator that equals 1 if a venture is in the last quartile of the distribution for the abnormal returns earned and zero otherwise, the coefficient of the interaction between $Post_{jt}$ and $Herd_{ijt}$ is not only positive but also statistically significant. Its magnitude suggests that acquirers acquiring ventures under herding are 13 percentage points more likely to earn abnormal returns than the other acquirers. Overall, these results provide an indication that acquirers imitate their predecessors to seize opportunities arising from the Israeli venture ecosystem rather than to follow the crowd.

⟨ Insert Table 3.11 about here ⟩

3.5 Conclusions

This paper asks whether the initial acquisition of a venture induces imitation among potential acquirers. In addressing this question, we fill an important gap. Although prior research has focused on the characteristics of target ventures and their investors, and on business cycles, as drivers of venture acquisitions, we contribute by providing evidence of herding among prospective acquirers. Furthermore, we illustrate that this herding behavior stems from acquirers' efforts to learn about opportunities in less familiar markets. Therefore, acquisition herding serves as a mechanism through which potential acquirers mitigate some of the information asymmetry associated with cross-market venture acquisitions.

We employ international acquisitions as an empirical setting. Using rich data on the population of Israeli ventures that obtained VC financing between 2002 and 2019, we evaluate how the initial acquisition of an Israeli venture by a foreign firm stimulates the demand for Israeli ventures by other foreign firms, comparing their reaction to that of domestic firms. Having applied machine learning methods to construct dyads of technologically similar ventures and estimated difference-in- differences and instrumental variable models, we find that the acquisition of a venture by a foreign company increases the chances that its peer is also acquired by a foreign company by 61%. Consistent with informational herding, whereby foreign acquirers imitate their predecessors to deal with uncertainties over market opportunities, we find that this effect is double that on the likelihood that a venture is acquired by a domestic firm.

We provide several additional results supporting our informational herding hypothesis. First, the effect on the likelihood that a venture is acquired by a foreign firm intensifies when we adopt more stringent criteria for defining dyads of technologically similar ventures. This result suggests that the information value of an initial acquisition is strongest when two acquisition targets develop close technologies. Similarly, the effect becomes null when the initial acquisition is undertaken by an Israeli firm whose background is likely different from that of a foreign acquirer. Next, we show that herding effects become stronger when an initial acquisition is enacted by a prominent foreign firm. Delving deeper into this finding, we further show that being associated with an initial prominent acquisition is more impactful than being associated with subsequent acquisitions. This result suggests that the accumulation of acquisition events is associated with a parallel accumulation of information regarding opportunities arising from a given entrepreneurial ecosystem, reducing the marginal value of herding behavior. Additionally, we find that the less informed foreign acquirers -namely, non-US acquirers and foreign acquirers without an R&D center in Israel- respond more strongly to prominent acquisitions of Israeli ventures than to non-prominent acquisitions, relative to the better informed foreign acquirers.

Our fine-grained data allow us to rule out several alternative interpretations. For instance, we show that our findings are not driven by VCs investing larger amounts in their portfolio ventures' value, making these companies more attractive to foreign acquirers. Indeed, we find that VCs do not invest larger amounts in their ventures after technologically similar peers have been acquired. Moreover, we show that ventures whose technologically similar peers were acquired by a foreign company sell at a higher price than their controls. This evidence speaks against the possibility that our results capture solely an increase in the supply of ventures seeking acquisition opportunities. Additionally, we show that our results hold after replacing subsector by year fixed effects with the more fine-grained technology keyword by year fixed effects. This last analysis addresses the concern that our results are driven by acquisition waves following specific technology shocks. Consistently, we show that after an Israeli venture is acquired, US ventures developing similar technologies as the acquired venture do not improve their acquisition chances relative to US ventures that produce dissimilar technologies. This last result further confirms that our herding effects are driven by firms reacting to technological opportunities in a specific ecosystem rather than firms responding to technological opportunities regardless of the location in which they are developed.

To bring our results full circle, we assess whether potential acquirers gain by imitating the behavior of their predecessors. Here, we find that acquirers earn relatively higher abnormal returns when they engage in herding. This finding confirms that herding allows acquirers to seize opportunities arising from a given ecosystem.

These findings have implications for both policymakers building or expanding their venture ecosystems and potential acquirers. One of the major obstacles policymakers around the world encounter is the limited availability of potential acquirers that could offer exit opportunities to domestic ventures. Our results show that an initial acquisition can generate a cascade effect, inducing imitation by other firms and improving the acquisition prospects of ventures embedded in a given ecosystem. Potential acquirers may rely on initial acquisitions to learn about opportunities in a given ecosystem and improve their competitive advantage. However, this strategy is profitable as long as imitation does not induce acquirers to make sub-optimal investments. Crucially for public policymakers, the study underscores the importance of fostering economic infrastructure that facilitates cross-border investments and cultivates international social networks. Such infrastructure holds the potential for substantial cascade effects and significant macroeconomic benefits.

To conclude, these insights open avenues for future research. For instance, future empirical investigation could extend our analyses to the behavior of intermediate investors. While we have some evidence that VCs respond by participating in a relatively larger number of later-stage rounds and a smaller number of early-stage rounds, future research could delve deeper into these VC reactions.

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3.6 Tables and figures

Table 3.1: Summary statistics

	Mean	SD	Min	Median	Max
venture sectors					
Cleantech	0.09	0.28	0	0	1
Communications	0.17	0.37	0	0	1
IT & Enterprise Software	0.23	0.42	0	0	1
Internet	0.21	0.41	0	0	1
Life Sciences	0.23	0.42	0	0	1
Miscellaneous Technologies	0.06	0.24	0	0	1
Semiconductor	0.03	0.16	0	0	1
venture-level financing statistics					
Raised funds from VCs	0.38	0.48	0	0	1
Raised funds from US VCs	0.16	0.37	0	0	1
Cum. amount of funds ($ mill.)	8.06	29.88	0	0.66	850
Cum. amount of US funds ($ mill.)	5.15	25.1	0	0	850
Cum. amount of US VC ($ mill.)	3.55	19.78	0	0	611.6
N rounds raised	1.72	1.19	1	1	10
Cum. number of US patents	1.23	5.49	0	0	191
venture-level exit statistics					
Had an Exit (IPO/Acquisition)	0.14	0.35	0	0	1
Had an IPO	0.02	0.14	0	0	1
Was Acquired	0.12	0.33	0	0	1
Was Acquired by foreign company	0.08	0.27	0	0	1
Was Acquired by US company	0.06	0.23	0	0	1
Was Acquired by Israeli company	0.04	0.2	0	0	1
Sales price ($ mill.)	111.08	691.77	0.13	25	15300
Observations			5725		

Notes: Descriptive statistics for the ventures in our sample. The ventures raised a financing round between 2002 and 2019 and were founded between 1998 and 2018. The sales price statistics were computed for the set of companies that were acquired and for which we have information on sales price. The *Raised funds from VCs* variable is a (0/1) indicator identifying ventures that raised funds from venture capitalists (VCs). The *Raised funds from US VCs* variable is a (0/1) indicator identifying ventures that raised funds from US VCs. *Cum. amount of funds* denotes the cumulative amount of funds a venture raised from establishment until 2019. To compute the cumulative amount of funds a venture raised from US investors (*Cum. amount of US funds*), we only summed those amounts raised during rounds in which at least one US investor participated. Similarly, the cumulative amount of funds a venture raised from US VCs (*Cum. amount of US VC funds*) was obtained by summing those amounts raised during rounds in which at least one US VC participated.

Table 3.2: Summary statistics at the venture-dyad level, by treatment

	(1) Treatment=1		(2) Treatment=0		(3)
	Mean	SD	Mean	SD	Diff.
Had an exit (IPO/Acquisition)	0.1411	0.3481	0.0903	0.2865	0.0508***
Had an IPO	0.0054	0.0730	0.0097	0.0979	-0.0043***
Was acquired	0.1339	0.3406	0.0792	0.2701	0.0547***
Was acquired by foreign company	0.0885	0.2840	0.0485	0.2149	0.0399***
Was acquired by US company	0.0635	0.2438	0.0343	0.1821	0.0292***
Was acquired by Israeli company	0.0455	0.2083	0.0307	0.1725	0.0148***
Sales price ($ mill.)	96.9456	422.3059	72.5511	146.3547	24.3945***
Cum. amount of funds ($ mill.)	10.8630	28.7546	8.7623	29.4244	2.1007***
Cum. amount of US funds ($ mill.)	5.7809	21.7008	4.6269	24.0389	1.1540***
Cum. amount of US VC funds ($ mill.)	3.8354	17.9611	2.9699	18.4428	0.8655***
Cum. number US patents	1.4963	5.8626	1.4587	5.5333	0.0375
Observations	16038		117160		

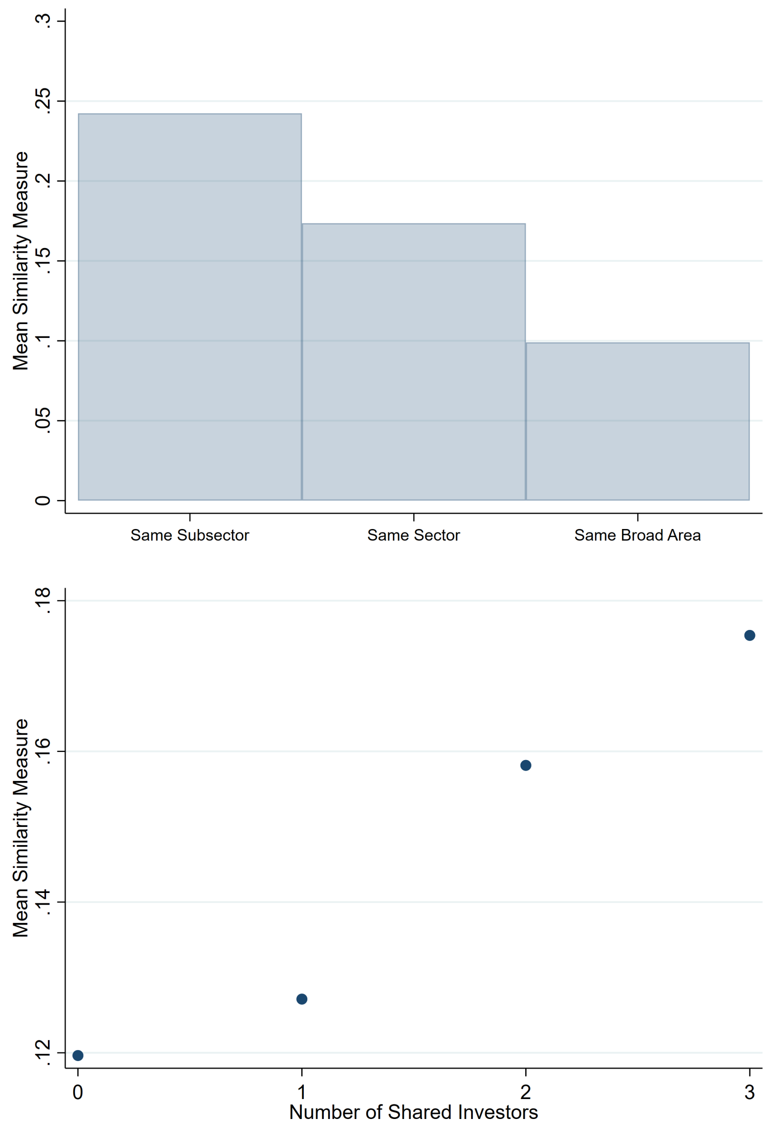
Notes: *Treatment* is equal to one if an observed venture is matched with a peer that is acquired by a foreign company and zero otherwise. In building the sample, we generate *g* groups of treated and control ventures such that each treated venture belonging to dyad *ij* is randomly assigned ten control ventures whose peers are not acquired by a foreign firm. We impose that the control ventures are established during the same year as the treated ventures, but in a different sector. We remove from the sample those dyads in which the observed company was established at least five years prior to its peer. Furthermore, we exclude from the sample those instances where the treatment occurs after a given venture *i* assigned to dyad *ij* and group *g* experiences an exit event (either an acquisition or an IPO). Additionally, we exclude ventures that share fewer than three technology keywords with their peers. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.3: Summary statistics at the venture-dyad-year level, by treatment

	(1) Treatment=1		(2) Treatment=0		(3)
	Mean	SD	Mean	SD	Diff.
Had an exit$_t$ (IPO/Acquisition)	0.0219	0.1463	0.0097	0.0981	0.0122***
Had an IPO$_t$	0.0008	0.0288	0.0010	0.0323	-0.0002*
Was acquired$_t$	0.0208	0.1426	0.0085	0.0920	0.0122***
Was acquired by foreign company$_t$	0.0137	0.1163	0.0052	0.0721	0.0085***
Was acquired by US company$_t$	0.0098	0.0987	0.0037	0.0607	0.0061***
Was acquired by Israeli company$_t$	0.0071	0.0837	0.0033	0.0574	0.0037***
Cum. amount of funds$_t$ ($ mill.)	9.3241	23.1524	6.1036	22.2645	3.2205***
Cum. amount of US funds$_t$ ($ mill.)	4.4347	17.4300	2.7611	18.5412	1.6736***
Cum. amount of US VC funds$_t$ ($ mill.)	2.8999	14.7057	1.7466	13.7265	1.1533***
Cum. number US patents$_t$	1.4188	5.0785	1.1713	4.3248	0.2475***
Observations	103391		1087876		

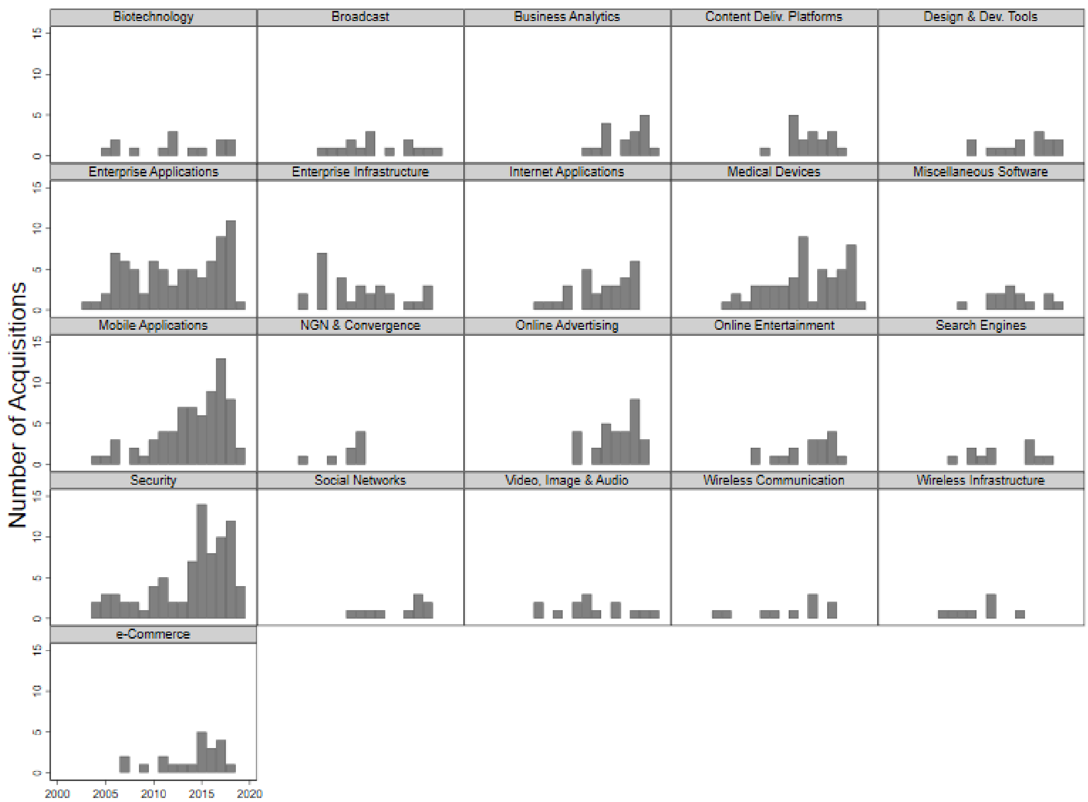
Notes: *Treatment* takes the value one after the peer of a treated venture is acquired by a foreign firm and zero otherwise. For details on the sample construction refer to the notes in Table 2a.

Figure 3.1: Assessing the technology similarity between dyadic peers



Notes: The figure at the top of the page shows how the similarity between two ventures in a dyad varies according to whether the ventures belong to the same subsector (a list of subsectors is provided in Table A1 of the Appendix), sector (cleantech, communications, IT & enterprise software, Internet, life sciences, semiconductors, and miscellaneous technologies), or broad area (cleantech, life sciences, Internet, and the remainder). We define the similarity between two ventures i and j in a dyad as: $\frac{NSharedTags_{ij}}{min(NTags_i, NTags_j)}$ that is, the ratio of the number of technology keywords that *i* and *j* share to the minimum number of keywords between *i* and *j*. This measure was calculated for all possible dyadic combinations of the 5,725 ventures belonging to our sample. The figure at the bottom plots the mean similarity measure over the number of investors that the ventures in a dyad have in common.

Figure 3.2: Acquisitions by sector and over time



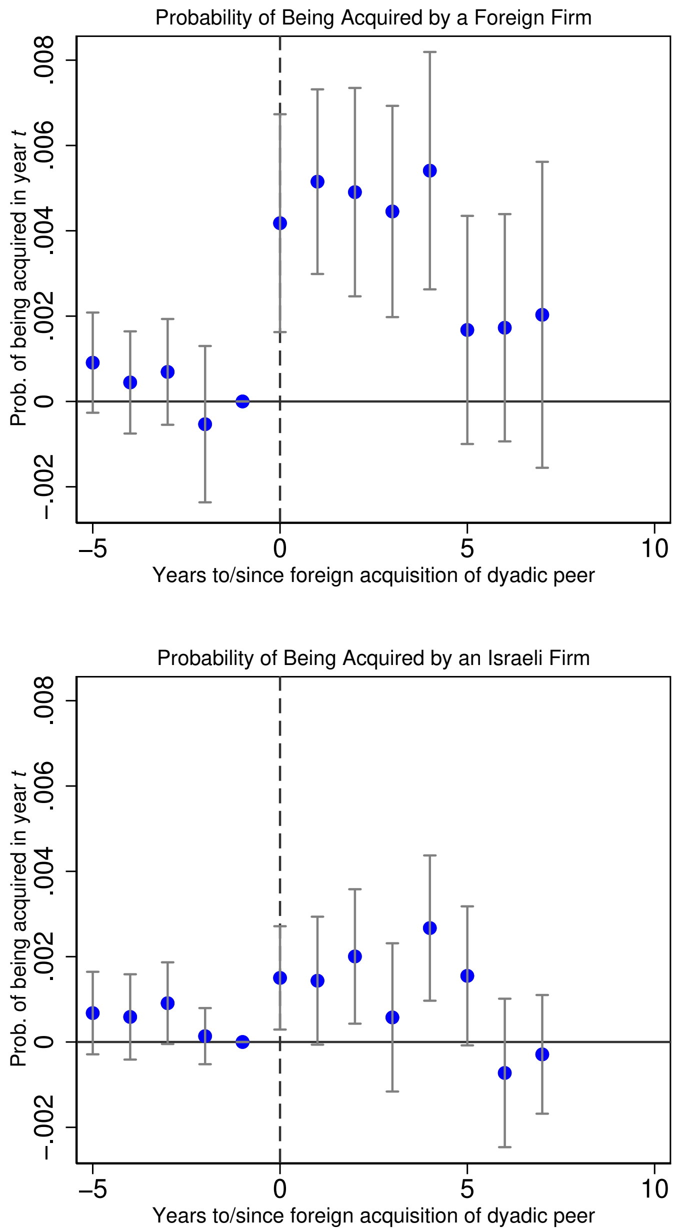
Notes: This figure depicts the number of acquisitions by subsector and over time. We only report those subsectors with an overall number of acquisitions above the mean.

Table 3.4: venture liquidity events after a peer is acquired by a foreign company

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by Foreign Firm	(4) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0193***	0.0171***	0.0106***	0.00646***
	(0.000794)	(0.000750)	(0.000724)	(0.000669)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00434***	0.00471***	0.00365***	0.00106***
	(0.000577)	(0.000529)	(0.000507)	(0.000314)
Obs. venture FEs	Y	Y	Y	Y
Peer venture FEs	Y	Y	Y	Y
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
Dyads	133198	133198	133198	133198
Groups of Treated-Control ventures	48237	48237	48237	48237
R2	0.128	0.131	0.124	0.148
Mean Outcome Variable	0.01078	0.00959	0.00596	0.00363

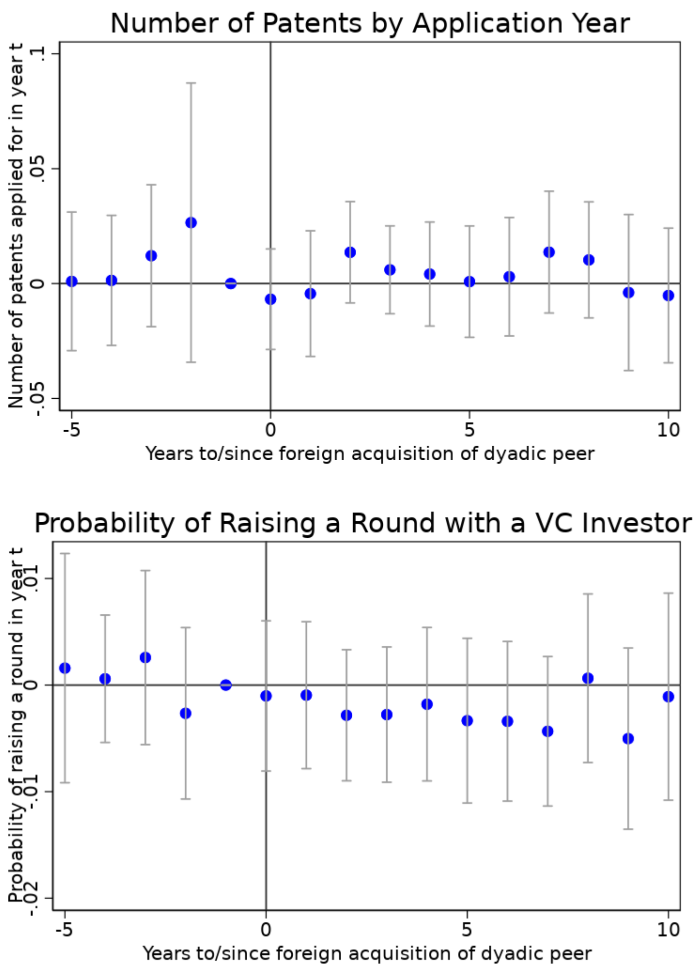
Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) either acquired or goes public via an IPO in year t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm$_i$* is an indicator that equals one if the peer *j* of a venture *i* is acquired by a foreign firm and zero otherwise. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group *g*, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) observed venture *i*; ii) peer *j*; iii) the *ij* dyad; iv) *i*'s subsector-by-year; v) *j*'s subsector-by-year; and vi) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Figure 3.3: The effect of an acquisition by a foreign firm on the Israeli market for acquisitions



Notes: This figure shows how the probability that a venture is acquired by a foreign firm (top) and the probability that a venture is acquired by an Israeli firm (bottom) in a given year change after a venture's technologically similar peer is acquired by a foreign firm. To generate these graphs, we modified Eq. (1) in the main text by substituting the $PostAcquisition_{gt}$ indicator with binary variables for each of the pre- and post-treatment years. We interacted these year indicators with *Peer Acq. by Foreign Firm*$_i$, which equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. In the graphs, we report the coefficients for these interactions. The vertical bars represent 95% confidence intervals. The coefficient for the year immediately before the acquisition event is set to 0 and displayed without a confidence interval because it is our baseline year.

Figure 3.4: Intermediary performance outcome measures before and after treatment



Notes: The top panel of this figure reports the results of a similar event study as the one in Figure 3, but for an observed venture's yearly number of US patent applications (top) and a venture's likelihood of receiving VC funding in a given year (bottom). For the latter event study, we only consider those treated ventures that were not acquired since acquired ventures mechanically stop raising funds and this would bias our results.

Table 3.5: Strengthening the criteria for selecting technologically similar dyads

	ij shares a relevant technology keyword					
	(1)	(2)	(3)	(4)	(5)	(6)
	Acquisition/IPO	Acquired	Acquired by Foreign Firm		Acquired by Israeli Firm	
Post Acquisition$_{gt}$	0.0202***	0.0170***	0.0106***	0.00915***	0.00648***	0.00553***
	(0.00110)	(0.000868)	(0.000979)	(0.00101)	(0.000873)	(0.000846)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00551***	0.00648***	0.00477***	0.00478***	0.00171**	0.00139**
	(0.00110)	(0.00117)	(0.00106)	(0.000785)	(0.000752)	(0.000546)
Obs. venture FEs	Y	Y	Y	Y	Y	Y
Peer venture FEs	Y	Y	Y	Y	Y	Y
Dyad FEs	Y	Y	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y		Y	
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y		Y	
Year FEs $\times$ Obs. venture Keyword FEs				Y		Y
Year FEs $\times$ Peer venture Keyword FEs				Y		Y
Treated-Control venture Group FEs	Y	Y	Y	Y	Y	Y
Observations	453070	453070	453070	4453070	453070	453070
Dyads	50017	50017	50017	50017	50017	50017
Groups of Treated-Control ventures	32490	32490	32490	32490	32490	32490
R2	0.128	0.132	0.127	0.244	0.145	0.269
Mean Outcome Variable	0.01065	0.00908	0.00565	0.00565	0.00342	0.00342

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture is: i) either acquired or goes public via an IPO in year t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (columns 3 and 4); and iv) acquired by an Israeli company (columns 4 and 6). Refer to the notes in Table 3. The results in this table are obtained from imposing the criteria that the dyad ij shares at least three technology keywords *and* that at least one of these keywords is among the three most relevant for describing i's and j's technology according to our machine learning algorithm (Please refer to Appendix A.1 for details regarding the algorithm). In columns 4 and 6, we replace the subsector (times year) fixed effects with fixed effects for the most relevant technology keyword -according to our machine learning algorithm- describing i's and j's technology. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.6: Likelihood that a venture is acquired by a foreign company after its peer is acquired by an Israeli company

	(1) Acquired by Foreign Firm
Post Acquisition$_{gt}$	0.00529***
	(0.000550)
Peer Acq. by Israeli Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.000748
	(0.000817)
Obs. venture FEs	Y
Peer venture FEs	Y
Dyad FEs	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y
Year FEs $\times$ Peer venture Subsector FEs	Y
Treated-Control venture Group FEs	Y
Observations	824186
Dyads	90442
Groups of Treated-Control ventures	29341
R2	0.124
Mean Outcome Variable	0.00708

Notes: This table reports the results from estimating a linear probability model for the likelihood that a venture i belonging to dyad ij is acquired by a foreign company in year t. *Peer Acq. by Israeli Firm*$_i$ is an indicator that equals one if the peer *j* of a venture *i* is acquired by an Israeli firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by an Israeli firm. We include fixed effects for: i) observed venture *i*; ii) peer *j*; iii) the *ij* dyad; iv) *i*'s subsector-by-year; v) *j*'s subsector-by-year; and vi) group *g* including a treated venture and its controls. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.7: Distinguishing between prominent and less prominent foreign acquisitions of peers

	Acquired by Foreign Firm	
	Prominent Acq. I (1)	Prominent Acq. II (2)
Post Prominent Acq.$_{gt}$	0.00650*** (0.000723)	0.0106*** (0.000933)
Peer Acq. by Prominent Foreign Firm$_i$ $\times$ Post Prominent Acq.$_{gt}$	0.00501*** (0.000769)	0.00814*** (0.00149)
Post Non-Prominent Acq.$_{gt}$	0.00665*** (0.000563)	0.0106*** (0.000711)
Peer Acq. by Non-Prominent Foreign Firm$_i$ $\times$ Post Non-Prominent Acq.$_{gt}$	0.00331*** (0.000541)	0.00335*** (0.000482)
Obs. venture FEs	Y	Y
Peer venture FEs	Y	Y
Dyad FEs	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y
Treated-Control venture Group FEs	Y	Y
Observations	1191267	1191267
R2	0.123	0.124

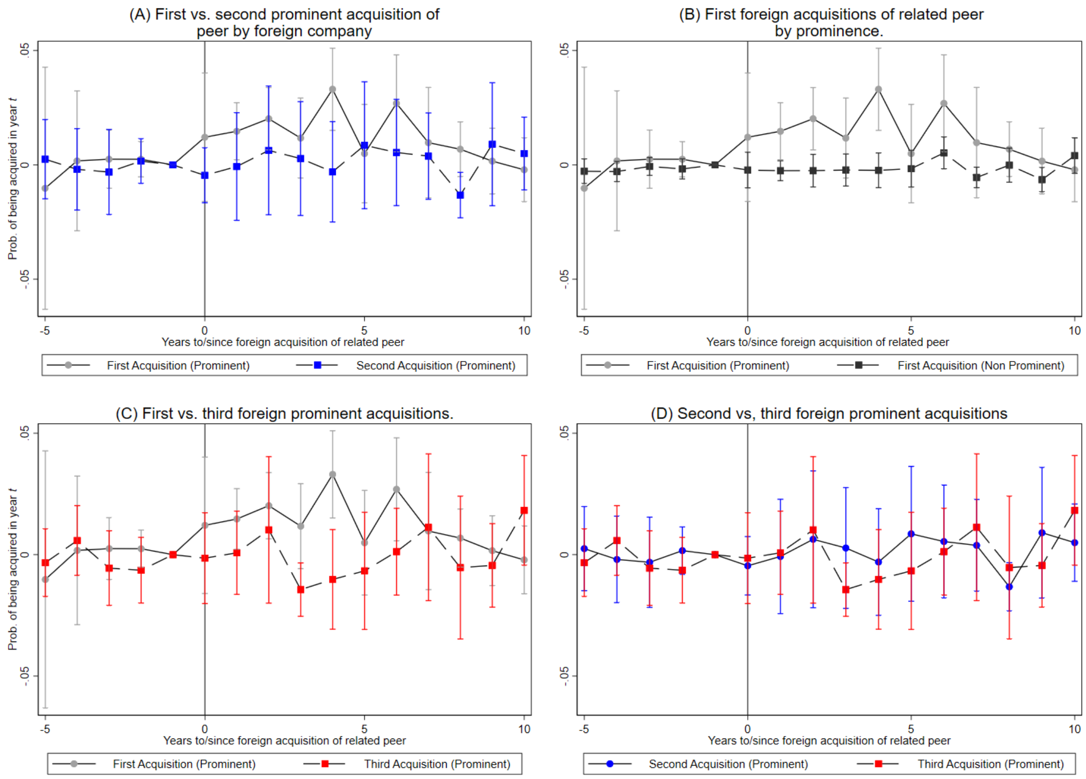
Notes: We assess how the effect of a peer being acquired by a foreign firm varies depending on whether the acquisition is prominent or not. In column 1, we identify as prominent acquisitions those enacted by prominent acquirers. In column 2, we refine the notion of prominent acquisitions and retain only those that received widespread media attention and whose sales price is above the sector median for a given year. To measure media attention, we collected from LexisNexis news reports concerning the acquisition of a venture that were published between six months before and six months after the acquisition event. Building on these data, a prominent acquisition is considered to have received widespread media attention if the number of news reports mentioning it is above the sector median. We implement the analysis by substituting in Eq. (1) the *Peer Acq. by Foreign Firm*$_i$ variable with two indicators, respectively identifying prominent and less prominent acquisitions of peers js. Additionally, the *Post Acquisition*$_{gt}$ indicators identify the post-treatment period, having distinguished between prominent and less prominent acquisitions. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.8: Exploring heterogeneity in the reaction to prominent and less prominent acquisitions of peers

	(1) Acquired by US Firm	(2) Acquired by EU or Asian Firm	(3) Acquired by Foreign Firm with R&D Center in Israel	(4) Acquired by Foreign Firm with no R&D Center in Israel
Post Prominent Acq.$_{gt}$	0.00826***	0.00235***	0.00234***	0.00826***
	(0.00107)	(0.000407)	(0.000528)	(0.000831)
Peer Acq. by Prominent Foreign Firm$_i$ $\times$ Post Prominent Acq.$_{gt}$	0.00570***	0.00244**	0.00177*	0.00638***
	(0.00108)	(0.00101)	(0.000853)	(0.000965)
Post Non-Prominent Acq.$_{gt}$	0.00792***	0.00270***	0.00221***	0.00841***
	(0.000853)	(0.000352)	(0.000426)	(0.000628)
Peer Acq. by Non-Prominent Foreign Firm$_i$ $\times$ Post Non-Prominent Acq.$_{gt}$	0.00274***	0.000610**	0.000979***	0.00237***
	(0.000389)	(0.000244)	(0.000209)	(0.000449)
Obs. venture FEs	Y	Y	Y	Y
Peer venture FEs	Y	Y	Y	Y
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
R2	0.123	0.125	0.128	0.125

Notes: This table explores heterogeneity in the reaction to prominent and less prominent acquisitions of venture peers. The outcomes examined are the likelihoods that observed ventures are acquired in t by: i) US firms (column 1); ii) European or Asian firms (column 2); iii) foreign firms with R&D centers in Israel (column 3); and iv) foreign firms with no R&D centers in Israel (column 4). We identify as prominent acquisitions those enacted by prominent acquirers and such that they received widespread media attention and the sales price is above the sector median. We include fixed effects for: i) observed venture *i*; ii) peer *j*; iii) the *ij* dyad; iv) *i*'s subsector-by-year; v) *j*'s subsector-by-year; and vi) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Figure 3.5: Acquisition dynamics



Notes: This figure illustrates how an observed venture's exit outcome responds to the earlier versus later foreign acquisitions of technologically similar peers, and further investigates whether any reaction depends on the prominence of a given acquisition. To perform this analysis, we condition on those instances in which the peers *j*s of a given venture *i* were acquired by a foreign company and rank these acquisition events from the earliest to the more recent. We then examine how *i*'s chances of being acquired by a foreign company vary pre- and post-treatment, comparing earlier to more recent treatments and, moreover, contrasting prominent with less prominent treatments. Panel A (top left) plots the year coefficients pre and post the prominent acquisition of *i*'s peer *j* by a foreign company, having distinguished between the earliest (i.e., first) and the second acquisition. As shown, the earliest acquisition produces stronger effects than the more recent one. Panel B (top right) zooms in on the earliest foreign acquisitions, contrasting prominent with non-prominent acquisitions. The treatment effects of an earliest acquisition are greater than zero only if such an acquisition is prominent. Panel C (bottom left) contrasts the earliest prominent acquisition of *i*'s peer *j* by a foreign company with the third of such events. The displayed pattern is similar to the one depicted in Panel A. Finally, Panel D (bottom right) compares the second to the third prominent acquisition of *i*'s peers. Here, we continue to find that earlier prominent acquisitions of *i*'s peers by foreign acquirers generate stronger effects than the more recent treatments, although the difference in effects is less pronounced.

Table 3.9: US venture acquisition events after an Israeli peer is acquired by a US company

	(1) Acquisition	(2) Acquisition
Post Israeli Acquisition$_{gt}$	0.03873***	0.03950***
	(0.00178)	(0.00187)
Tech. Similar$_i$ $\times$ Post Israeli Acq.$_{gt}$	0.00224	0.0006
	(0.00137)	(0.00394)
Obs. venture FEs	Y	Y
Peer venture FEs	Y	Y
Dyad FEs	Y	Y
Year FEs $\times$ US venture Tech. FEs	Y	Y
Year FEs $\times$ Israeli venture Tech. FEs	Y	Y
Dyads	26786	26786
Groups of Treated-Control ventures	232	232

Notes: This table reports the results from estimating a linear probability model for the likelihood that a US venture i belonging to dyad ij is acquired in year t. To construct the dyads, we considered all Israeli ventures that were acquired by a US company. We identified their profile in the Crunchbase database. We successively generated dyads of Israeli-US ventures. The US ventures were matched with the Israeli ones as follows. We randomly selected a sample of US ventures sharing at least three technology keywords (assigned by Crunchbase) with the Israeli companies and a sample of US ventures sharing less than three keywords. If ventures imitate each other to take advantage of technological opportunities regardless of where they emerge or if they respond to the same technology shocks without mimicry, the acquisition prospects of the first set of US ventures should be positively related to the acquisition of the Israeli companies -given technological closeness- relative to the second set, which represents the control group. We further imposed that the US companies should be founded within five years from the Israeli ventures' inception and should be in California, Massachusetts, or New York. Finally, we excluded those US companies that had an exit prior to the acquisition date of the associated Israeli company. In the model, *Post Israeli Acquisition*$_{gt}$ is a (0/1) indicator that becomes 1 after an Israeli venture is acquired, for all the US ventures associated with the Israeli company. *Tech. Similar*$_i$ is an indicator identifying all the US ventures sharing at least three technology keywords with the associated Israeli venture. In column 2, *Tech. Similar*$_i$, instead, identifies all the US ventures sharing at least four technology keywords. We include fixed effects for venture *i*, peer *j*, the *ij* dyad and for the most relevant technology keywords -describing i and j- times year. Standard errors are multi-way clustered by year, acquired Israeli venture, and associated US venture. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.10: venture sales price

	(1) Sales Price (log)	(2) Sales Price (indicator)
Peer Acq. by Foreign Firm$_i$	0.127	0.0363**
	(0.116)	(0.0169)
Cum. amount of funds - obs. venture (log)	0.448***	0.150***
	(0.120)	(0.0337)
Cum. amount of patents - obs. venture (log)	0.265**	0.0950**
	(0.104)	(0.0336)
Cum. amount of funds - peer venture (log)	0.0211	0.00438
	(0.0217)	(0.00779)
Cum. amount of patents - peer venture (log)	0.00721	0.0231
	(0.0510)	(0.0187)
Obs. venture Exit Year FEs $\times$ Sector FEs	Y	Y
Obs. venture Founding Year $\times$ Sector FEs	Y	Y
Treated-Control venture Group FEs	Y	Y
Groups of Treated-Control ventures	696	1380
Observations	1438	2908
R2	0.863	0.738

Notes: This table reports the results from estimating Eq. (2). We perform a cross-section analysis to assess how an observed venture's sales price varies depending on whether its peer was acquired by a foreign company. We limit the analysis to those dyads *ij* wherein the observed company *i* was acquired. The dependent variable in column 1 is the natural logarithm of an acquired venture's sales price. For this analysis, we exclude those dyads in which there is missing information on *i*'s sales price. The dependent variable in column 2 is an indicator identifying ventures that are above the median of the sectorial distribution of sales prices. This time, the indicator is set to zero for those acquired ventures with missing sales price information. According to Nanda and Rhodes-Kropf (2013), missing values should correspond to cases in which ventures were acquired at a negligible price. This is a plausible assumption. For example, Table A9 reports that acquired ventures with missing sales price information raise smaller VC amounts than acquired ventures with sales price. information. Standard errors (in parentheses) are multi-way clustered by groups of treated and control ventures and by *i*'s establishment year. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3.11: Acquirers' abnormal returns under herding

	(1)	(2)
	Cumulative Abnormal Returns	
Post	0.000247	0.03561
	(0.0019)	(0.0033)
Herd	0.00383	-0.01586
	(0.0127)	(0.0889)
Post $\times$ Herd	0.0125	0.12557*
	(0.0142)	(0.07394)
FirstAcq.	0.00626	0.05335
	(0.00828)	(0.06089)
Post $\times$ FirstAcq.	0.00268	0.00036
	(0.0101)	(0.0551)
Observations	6451621	6451621

Notes: This table reports the results from estimating a linear regression model for stocks' cumulative abnormal returns. In column 1, the dependent variable is the cumulative abnormal return on stock i for day t around acquisition j. The estimation period is from $t = -5$ to $t = +5$, relative to the announcement of an acquisition j, day $t = 0$. In column 2, the dependent variable is an indicator that equals 1 if a venture is in the last quartile of the cumulative abnormal return distribution. $Herd$ is an indicator for whether stock i belongs to the acquirer involved in acquisition j, and this acquisition follows prior acquisitions in the same technology space. $FirstAcq.$ is an indicator for whether stock i is of the acquirer involved in acquisition j, and this acquisition is the first acquisition in a given technology space. $Post$ identifies the post-acquisition period for acquisition j. We cluster standard errors at the acquisition event level. Standard errors are clustered at the acquisition event level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

3.7 Appendix

Table A3.1: List of subsectors (as defined by IVC)

Cleantech:	**Internet**:
Agrotech	Content Delivery Platforms
Energy	Content Management
Environment	E-Learning
Materials	Internet Applications
Water Technologies	Internet Infrastructure
Communications:	Online Advertising
Broadband Access	Online Entertainment
Broadcast	Search Engines
Enterprise Networking	Social Networks
Home Networking	E-commerce
Mobile Applications	**Life Sciences**:
Mobile Infrastructure	Biotechnology
NGN & Convergence	Digital Health
Optical Networking	Medical Devices
Security	Pharmaceuticals
Telecom Applications	**Semiconductors**:
VoIP & IP Telephony	Fabrication & Testing
Wireless Applications	Manufacturing Equipment & EDA
Wireless Infrastructure	Memory & Storage
IT & Enterprise Software:	Miscellaneous Semiconductors
Business Analytics	Network Processors
Content Delivery Platforms	Processors & RFID
Design & Development Tools	Security Semiconductors
Enterprise Applications	Video, Image & Audio
Enterprise Infrastructure	Wireless Communication
Miscellaneous Software	Wireline & Home Networking
Security	**Miscellaneous Technologies**:
Hardware	Defense
	Industrial Technologies
	Miscellaneous
	Nanotechnology

Table A3.2. Covariate Balance Analysis

	(1)	(2)
	Treatment=1	
Amount of Funds Raised (log)	0.0161***	0.00107
	(0.00183)	(0.00129)
Amount of Funds From US Investors (log)	0.000875	-0.00120
	(0.00155)	(0.00159)
Year FEs × Obs. venture Subsector FEs		Y
Year FEs × Peer venture Subsector FEs		Y
Treated-Control venture Groups FEs		Y
Observations	1191267	1191267
R2	0.00350	0.405

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is treated. As reported in column (1), there is a positive correlation between having a peer acquired by a foreign company and the total amount of funds raised. The correlation coefficient drops to approximately zero and is no longer statistically significant when we include fixed effects for *i*'s subsector-by-year, *j*'s subsector-by-year, and group *g* including a treated venture and its controls. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.3: List of prominent acquirers

Amazon
AOL
Apple
Broadcom
CA Technologies
Cisco
Dell
Dropbox
eBay
Facebook
General Electric
Google
Hewlett-Packard
IBM
Intel
Lucent Technologies
Miscrosoft
Mitsubishi
Medtronic
Merck
Monsanto
Motorola
Nielsen
Oracle
Palo Alto
PayPal
Qualcomm
STMicroelectronics
Stryker
Xerox
Yahoo!

Table A3.4. venture liquidity events after a peer is acquired by a foreign company: Distinguishing between larger and smaller foreign acquirers

	(1) Acquired by Large Foreign Firm	(2) Acquired by Smaller Foreign Firm
Post Acquisition$_{gt}$	0.00401***	0.00661***
	(0.000423)	(0.000508)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00144***	0.00221***
	(0.000321)	(0.000451)
Dyad FEs	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y
Treated-Control venture Groups FEs	Y	Y
Observations	1191267	1191267
Dyads	133198	133198
Groups of Treated-Control ventures	48237	48237
R2	0.129	0.123
Mean Outcome Variable	0.00187	0.00409

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is acquired in t by: i) a large foreign firm (column 1); and ii) a small foreign firm (column 2). *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) the *ij* dyad; ii) *i*'s subsector-by-year; iii) *j*'s subsector-by-year; and iv) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.5. Distribution of acquisitions by sector

	(1) Foreign acq.		(2) Domestic acq.		(3)
	mean	s.d.	mean	s.d.	diff.
Cleantech	0.0211	0.1438	0.0276	0.1643	0.0066
Communications	0.2037	0.4033	0.2258	0.4191	0.0221
Internet/IT	0.5550	0.4975	0.5253	0.5005	-0.0297
Life Sciences	0.0281	0.1655	0.0461	0.2101	0.0180
Medical Devices	0.0679	0.2519	0.0968	0.2963	0.0289
Miscellaneous Technologies	0.0375	0.1901	0.0507	0.2199	0.0132
Semiconductors	0.0867	0.2817	0.0276	0.1643	-0.0590***
Observations	427		217		644

Notes: We report the distribution of acquisitions by sector, distinguishing between foreign and domestic acquisitions of Israeli ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.6. venture liquidity events after a peer is acquired by a foreign company: Excluding semiconductor ventures

	(1) Acquired by Foreign Firm	(2) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0101***	0.00665***
	(0.000766)	(0.000715)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00363***	0.00132***
	(0.000591)	(0.000351)
Dyad FEs	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y
Treated-Control venture Groups FEs	Y	Y
Observations	1136486	1136486
Dyads	127835	127835
Groups of Treated-Control ventures	47586	47586
R2	0.120	0.133
Mean Outcome Variable	0.00578	0.00366

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) acquired by a foreign company (column 1); and ii) acquired by an Israeli company (column 2). We exclude semiconductor companies from the sample. *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer *j* of a venture *i* is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) the *ij* dyad; ii) *i*'s subsector-by-year; iii) *j*'s subsector-by-year; and iv) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.7. venture likelihood of being acquired by a foreign company after a peer is also acquired by a foreign company: Having excluded security ventures from the sample

	(1) Acquired by Foreign Firm
Post Acquisition$_{gt}$	0.00984***
	(0.000876)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00321***
	(0.000582)
Dyad FEs	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y
Year FEs $\times$ Peer venture Subsector FEs	Y
Treated-Control venture Groups FEs	Y
Observations	1141712
Dyads	127565
Groups of Treated-Control ventures	47693
R2	0.123
Mean Outcome Variable	0.0054865

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is acquired in t by: i) a large foreign firm (column 1); and ii) a small foreign firm (column 2). *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) the *ij* dyad; ii) *i*'s subsector-by-year; iii) *j*'s subsector-by-year; and iv) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.8. Likelihood that an acquired venture has sales price information

	(1) Has Sales Price Information
Cum. amount of funds - obs. venture (log)	0.148***
	(0.0305)
Cum. amount of patents - obs. venture (log)	-0.00939
	(0.0350)
Cum. amount of funds - peer venture (log)	-0.000542
	(0.00444)
Cum. amount of patents - peer venture (log)	0.00677
	(0.0135)
Obs. venture Exit Year FEs $\times$ Sector FEs	Y
Obs. venture Founding Year $\times$ Sector FEs	Y
Treated-Control venture Group FEs	Y
Observations	2908
R2	0.773

Notes: This table reports the results for the likelihood that an acquired venture has sales price information. We perform a cross-section analysis and limit the analysis to those dyads *ij* wherein the observed company *i* was acquired. The dependent variable in column 1 is the natural logarithm of an acquired venture's sales price. Standard errors (in parentheses) are multi-way clustered by groups of treated and control ventures and by *i*'s establishment year. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.9. venture liquidity events after a peer is acquired by a foreign company: Truncating the sample to include only the first two years after the treatment occurs

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by Foreign Firm	(4) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0184***	0.0163***	0.0101***	0.00619***
	(0.000957)	(0.000900)	(0.000895)	(0.000599)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00316***	0.00353***	0.00254***	0.000998**
	(0.000573)	(0.000521)	(0.000597)	(0.000449)
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	734038	734038	734038	734038
Dyads	133198	133198	133198	133198
Groups of Treated-Control ventures	48237	48237	48237	48237
R2	0.224	0.227	0.217	0.239
Mean Outcome Variable	0.0084641	0.00755	0.0047314	0.0028187

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) the *ij* dyad; ii) *i*'s subsector-by-year; iii) *j*'s subsector-by-year; and iv) group *g* including a treated venture and its controls. We truncate the sample to include only the first two years after the treatment occurs. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.10. venture liquidity events after a peer is acquired by a foreign company: Adding time-varying controls

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by Foreign Firm	(4) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0187***	0.0165***	0.0102***	0.00635***
	(0.000784)	(0.000747)	(0.000728)	(0.000657)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00420***	0.00454***	0.00359***	0.000955***
	(0.000513)	(0.000464)	(0.000456)	(0.000326)
Time Varying Controls	Y	Y	Y	Y
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
Dyads	133198	133198	133198	133198
Groups of Treated-Control ventures	48237	48237	48237	48237
R2	0.130	0.134	0.127	0.149
Mean Outcome Variable	0.01078	0.00959	0.00596	0.00363

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group *g*, after the peer j of a treated venture is acquired by a foreign firm. We control for: the cumulative amount of funds raised by i and j (and the corresponding interaction), the cumulative amount of US VC funds raised by i and j (including the interaction), and the cumulative number of US granted patents i and j applied for (including the interaction). We include fixed effects for: i) the *ij* dyad; ii) *i*'s subsector-by-year; iii) *j*'s subsector-by-year; and iv) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.11. venture liquidity events after a peer is acquired by a foreign company: Having drawn the control group from ventures belonging to the same sector, but different subsector, as the treated ventures

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by US Firm	(4) Acquired by US Firm
Post Acquisition$_{gt}$	0.0268***	0.0254***	0.0167***	0.00878***
	(0.00191)	(0.00195)	(0.00170)	(0.00126)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00169	0.00145	0.00129**	0.000165
	(0.000972)	(0.000904)	(0.000551)	(0.000780)
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	290080	290080	290080	290080
Dyads	104703	104703	104703	104703
Groups of Treated-Control ventures	22441	22441	22441	22441
R2	0.135	0.137	0.132	0.155
Mean Outcome Variable	0.01481	0.01406	0.00898	0.00508

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a foreign firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a foreign firm. We include fixed effects for: i) the *ij* dyad; ii) a given year-*i*'s subsector; iii) a given year-*j*'s subsector; and iv) group g including a treated venture and its controls. We draw the control group from ventures operating in the same sector, but different subsector, as the treated ventures. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3.12. venture liquidity events after a peer is acquired by a US company

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by US Firm	(4) Acquired by US Firm
Post Acquisition$_{gt}$	0.0195***	0.0173***	0.00820***	0.00628***
	(0.000887)	(0.000847)	(0.000895)	(0.000827)
Peer Acq. by US Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00469***	0.00561***	0.00302***	0.00158***
	(0.000621)	(0.000558)	(0.000502)	(0.000348)
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. venture Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer venture Subsector FEs	Y	Y	Y	Y
Treated-Control venture Group FEs	Y	Y	Y	Y
Observations	983062	983062	983062	983062
Dyads	104703	104703	104703	104703
Groups of Treated-Control ventures	35588	35588	35588	35588
R2	0.124	0.128	0.119	0.145
Mean Outcome Variable	0.01126	0.01003	0.00448	0.00371

Notes: This table reports the results from estimating linear probability models for the likelihood that a venture i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a US company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by US Firm*$_i$ is an indicator that equals one if the peer j of a venture i is acquired by a US firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the ventures in a treated-control group g, after the peer j of a treated venture is acquired by a US firm. We include fixed effects for: i) the *ij* dyad; ii) a given year-*i*'s subsector; iii) a given year-*j*'s subsector; and iv) group *g* including a treated venture and its controls. Refer to the notes in Table 2 for a description of how the *g* groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control ventures. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.